Brain Computer Interfaces for Communication

Moving beyond the visual speller

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Chapter 1

Introduction

Our brain constantly interacts with the world by controlling our bodies and the evolution of the human brain has been toward an increased control of body movement. More precise movement of hands and arms allowed us to use complex tools and the increased control over our articulatory system allowed us to communicate with each other and share ideas, learn, and grow beyond other species. However, there are some diseases and conditions where this strong link between the body and the brain is severed. In these situations, the brain still functions and all cognitive abilities are intact, but the brain is no longer able to control the body to express or effectuate these abilities. Diseases like Multiple Sclerosis (MS), Amyotrophic Lateral Sclerosis (ALS) or high spinal cord lesions all lead to a loss of body control often with only minor cognitive deficiencies (Amato 2001, Ringholz et al. 2005). For these patients the question arises, is there a way to restore this connection, to allow them to effectuate change in the world again? Although not nearly as well as the body, a Brain-Computer Interface could allow this.

1.1 What is Brain Computer Interfacing?

The field of Brain-Computer Interface (BCI) research is a multidisciplinary field encompassing cognitive neuroscience, machine learning and human computer interaction. The goal of the field is to develop user interfaces that are controlled only by brain activity. This enables patients that are paralysed and not able to use the conventional ways of controlling a computer to use the interface. A BCI (van Gerven et al. 2009, Wolpaw et al. 2002) translates measured brain activity into output commands. These output commands can be used for various purposes. First, the control of a computer (Wolpaw and McFarland 2004, Scherer et al. 2008), or external devices, for instance a wheel chair (Perrin et al. 2010, Carlson and del R. Millan 2013). This allows patients to control an external device, when they have no other means, i.e., muscles or peripheral nervous system, to do this. Second, the output commands can be used for communication (Farwell and Donchin 1988, Birbaumer et al. 1999, Blankertz, Dornhege, Krauledat, Schröder, Williamson, Murray-Smith and Müller 2006), allowing patients that were previously not able to communicate due to paralysis to do so again. Third, the output commands can be used for rehabilitation (Pfurtscheller et al. 2008, Daly et al. 2009, Silvoni et al. 2011, Severens et al. 2012). In such a BCI the output commands are often used to move parts of the patients body. For example, when after a stroke movement of the arm is impaired, a BCI detects attempted arm movements and moves the arm. This way the brain receives proprioceptive information, which could help in rehabilitation. The above mentioned uses of the output commands are all based on the premise that the user actively uses the BCI. The fifth way a BCI can be used is in a more passive way, where the BCI measures brain activity to determine for instance level of workload or attention and give warning when it reaches a critical level (Kohlmorgen et al. 2007, Chavarriaga and Millan 2010, Brouwer et al. 2012).

Neurofeedback is closely related to BCIs for rehabilitation. In neurofeedback similar techniques are used to provide feedback on a subject's brain activity with the goal of changing this activity. This is mostly used in a clinical setting where it is used as a therapy for neurological disorders by so called 'normalization' of the brain signature. When there is a difference in (resting-state) brain activity between healthy subjects and patients, neurofeedback can be used to move the brain activity of the patient towards that of the healthy subject. This is hypothesized to reduce or remove the symptoms of the patient. Neurofeedback has been researched in the context of ADHD (Gevensleben et al. 2009), depression (Linden et al. 2012), Parkinsons disease (Subramanian et al. 2011) and more. Though neurofeedback often has an effect on the measured brain activity, it does not always result in behavioral effects (Logemann et al. 2010, Staufenbiel et al. 2014, van Dongen-Boomsma et al. 2013) and caution must be taken to make sure that the effects found in neurofeedback studies are not caused by a placebo effect.

1.2 Measuring brain activity

The brain activity used by a BCI can be measured by different devices. The most commonly used method is the Electroencephalogram (EEG) (Berger 1929). EEG measures the electrical signals produced by the brain by placing electrodes on the scalp. The advantages of EEG for BCI are that the device is portable, relatively inexpensive and the measurement is non-invasive, i.e., it does not require surgery. Therefore, this is very suitable for use both in the lab and at home. BCI's using EEG data have been developed by, amongst others, Farwell and Donchin (1988), Birbaumer et al. (1999). Similar to EEG is the, also non-invasive, Magnetoencephalogram (MEG) (Cohen 1968).

In MEG the magnetic fields of the electrical signals of the brain are measured using super-conducting detectors. These detectors must be cooled using liquid helium, making the device large and very expensive. Therefore, this method is only usable in the lab. Mellinger et al. (2007), Bahramisharif et al. (2010) have developed BCIs based on MEG. Both EEG and MEG are very accurate in the timing of brain response, but not very accurate in the spatial location of the response. Another non-invasive method is functional Magnetic Resonance Imaging (fMRI) (Bandettini et al. 1992, Kwong 1992, Ogawa et al. 1992). fMRI measures the blood oxygenation levels of the blood and blood flow in the brain. This is an indirect measure of where increased brain activity is assumed to be when there is an increase in oxygenated blood in a certain brain region. The changes in blood oxygenation and blood flow, also called hemodynamic response, are measured by exciting hydrogen atoms and measuring the decay of this excitation. This requires a strong magnetic field, e.g., 1,5 or 3 Tesla with a uniform direction, which is created by a current going through a super-conductive coil. As with MEG, to achieve super-conduction the coil is cooled with liquid helium, making the MRI-scanner also large and very expensive. For more information on fMRI, see Huettel et al. (2009). In contrast to EEG and MEG, fMRI is spatially very accurate, but not very accurate in timing, due to it being dependent on a relatively slow, indirect, measure of activity (the hemodynamic response). fMRI has been used in building BCIs by Weiskopf et al. (2004) and Hinterberger et al. (2005). Another method of measuring brain activity that also measures blood flow in the brain is Near Infra-red Spectroscopy (NIRS) (Ferrari et al. 1985). NIRS measures the hemodynamic response like fMRI, but uses infra-red light emitters and sensors on the scalp instead of a strong magnetic field. The device is portable and relatively inexpensive, making it useful both in the lab and at home. It is spatially less accurate than fMRI and can only image sources in the superficial cerebral cortex, i.e., near the skull. It has a similar temporal sensitivity as fMRI. This technique has been used to develop BCIs by Coyle et al. (2007), Fazli et al. (2012), and Blokland et al. (2013). The Electrocorticogram (ECoG) (Jasper and Penfield 1949) can also be used to measure brain activity. This technique measures the brain activity from under the skull, either on the dura or directly on the brain. It has very high spatial and high temporal resolution. The device is portable, however due to the electrodes being placed under the skull, it is an invasive method. ECoG has been used in BCI development by Schalk et al. (2007) and Blakely et al. (2008). A last method is single-cell recordings, where single neurons or a small group of neurons is measured by pushing micro-electrode-arrays into the brain itself (Marg and Adams 1967). This has the advantage of very high spatial resolution (micron level) and temporal resolution. It is also a very invasive method and there are still issues with the long-term use of these micro-arrays. Kennedy and Bakay (1998) and Hochberg et al. (2006) have developed BCIs that use micro-electrode arrays. For an overview of all above mentioned methods, see Table 1.1.

In the research described in this thesis EEG is used to measure brain activity. This method was chosen mostly because of the portability and the non-invasiveness of the method, which are both important aspects when the developed BCI's are to be used in a patient's home.

Table 1.1: **Methods for measuring brain activity.** The different methods described in the text are summarized by their important characteristics: temporal and spatial resolution, whether the method is portable and wether it is invasive.

Method	Abbrev.	Resolution		Portable	Invasive
		Temporal	Spatial		
Electroencephalogram	EEG	high	low	✓	✗
Magnetoencephalogram	MEG	high	medium	✗	✗
functional Magnetic Resonance Imaging	fMRI	low	high	✗	✗
functional Near Infrared Spectroscopy	fNIRS	low	low	✓	✗
Electrocorticogram	ECoG	high	high	✓	✓
Single-cell recordings		very high	high	✓	✓

1.3 Tasks and brain activity

Over the last decades much research has been conducted in the field of cognitive neuroscience. This research resulted in a (not exhaustive) list of replicable brain signatures which correlate with the brain performing a particular task, that can be of use to make brain-computer interfaces. These signatures can be split into those that are the response to stimuli (evoked) and those that are voluntarily generated by the subject (induced). Commonly used evoked signatures include the P300, steady state evoked potentials (SSEPs), mismatch negativity (MMN), and the error related potential (ErrP). Commonly used induced signatures include the event related desynchronization/synchronization (ERD/ERS), alpha power, and slow cortical potentials.

For the evoked signatures the P300 (Farwell and Donchin 1988, Linden 2005, Polich 2007) is a positive going wave around 300 ms after stimulus onset. The P300 is elicited by an oddball task, where the subject is presented with two types of stimuli: standard stimuli and target stimuli. The target stimuli occur less often than the standard stimuli, and have a certain saliency for the subject, e.g., they need to count the number of target stimuli that occur in a sequence. When the target stimulus is consciously observed, the P300 occurs. The steady state evoked potentials (Regan 1977) occur when the subject is presented with a stimulus of a fixed frequency for a longer period of time. The brain area that processes the stimulus starts to oscillate in the same frequency. Steady state responses can be evoked in the visual, auditory and tactile modalities, and are observed in the visual, auditory, and somatosensory cortices respectively. The mismatch negativity (Näätänen et al. 2007, Brandmeyer et al. 2013) is part of the primary auditory response to change, peaking around 200 ms after change onset. The MMN occurs when subjects are able to form a representation of aspects of an auditory stimulus and a new stimulus is presented that violates this representation. The error related potential (Ferrez and Millán 2005, Chavarriaga and Millan 2010) occurs when subjects are aware of an error they made or someone else made.

For the induced signatures the event-related desynchronization and synchronization (ERD/ERS) occur when subjects move (Pfurtscheller and Lopes da Silva 1999). The ERD and ERS not only occur when subjects make movements, but also when they imagine the movement or in the case of patients when they attempt to move. Changes in alpha-band oscillations in different brain regions occur when subjects focus their attention (van Gerven and Jensen 2009, Bahramisharif et al. 2010). For example, when subjects focus their attention on the left visual field, there is an increase in the alpha power in the left hemisphere and a decrease in the right hemisphere. Alpha-band oscillations have been proposed as an attention suppression mechanism and are invoked to actively suppress processing of irrelevant information (Foxe and Snyder 2011). In the case of visual attention to one hemifield this leads to an increase in alpha power in the ipsilateral hemisphere. This change in alpha power not only occurs in the visual modality, but also in the auditory and tactile modalities. Another induced signature is the slow cortical potential (Birbaumer et al. 1999). It is a positive or negative going wave of about two to four seconds. Using operant conditioning subjects can be trained to voluntarily raise or lower their SCP.

Of course there are many other tasks subjects could perform. For some of them the brain signature that accompanies them is known, while for others this is not the case. Part of BCI research focuses on finding new tasks that subjects can perform that result in reliable and replicable brain signatures that could be used in a BCI.

1.4 Classification

The previous sections discussed the measurement and elicitation of brain activity, but how is the task the subject is performing detected or labeled, e.g. is the measured brain response a P300 or not? To do this, signal processing and classification techniques (Bishop 2006) are used. Classification falls within the machine learning part of artificial intelligence and concerns itself with automatically labelling segments of data. There are two types of classification algorithms: unsupervised and supervised algorithms. Unsupervised algorithms try to find the labels from raw, unlabelled data. The most common unsupervised learning methods are clustering algorithms that cluster data together based on certain aspects or criteria. Supervised algorithms are trained by providing them with examples where the labels are known. They extract the information or aspects of the data that allows for prediction of the class for unseen data. There are many supervised algorithms, e.g., neural networks (NN), support vector machines (SVM), discriminant analysis (DA), and logistic regression. The last of these algorithms is used in all chapters of this thesis. To be precise, a L2-regularized logistic regression classifier is used as it has been shown to perform well and has the advantage of producing probabilistic predictions which is useful in situations where many predictions must be combined – such as the spellers in chapters 2, 3, and 5. The regularization is necessary to prevent over-fitting.

Some important terms that are used in describing classifiers and their outcomes are: classes, epochs, features, labels, examples, regularization, and chance-level. Classes are the categories the classifier is able to distinguish. Many classifiers can distinguish two classes and are called binary classifiers. They group the data into two categories, e.g., P300 or not P300. An epoch is an individual piece of data which should be classified – that is given a predicted class label. Each epoch contains a set of individual features which are used by the classifier to categorize the epoch. For this work each feature was the voltage measured at an individual EEG electrode at a particular point in time. A label is attached to an epoch to indicate to which class it belongs. Epochs in the training set have known labels, while in the test set the labels need to be provided by the classifier. Examples are the epochs for which the label is already known and are used to train the classifier. Regularization is a penalty on complex solutions of the classifier to prevent over-fitting and increase the generalizability of the classifier. Chance-levels indicates the percentage correct when the labels are randomly assigned. In the simple case with a uniform prior probability distribution of the classes and balanced data, this is given by $\frac{1}{N} \cdot 100\%$, where N is the number of classes. In the case of a binary classifier, $N = 2$, so the chance-level is 50%.

Using a supervised algorithm consists of two steps, the training of the algorithm and the application of the algorithm to new data (with unknown labels). During the training of the algorithm, two types of parameters are set: the parameters that determine the distinction between the two classes, and the hyper-parameters, which influence how the aforementioned parameters are set. Regularization is applied here to prevent over-fitting. When over-fitting occurs, the classifier learns the noise in the data as well as the underlying class-relevant distinction. New data will have different noise making the classifier perform poorly. Regularization penalizes complex solutions, forcing the classifier to only learn the class-relevant distinction and ignore the noise. This leads to less over-fitting and better generalizability of the solution. To determine the influence of the different settings of the hyper-parameters, cross-validation is applied. In cross-validation the data is split into two sets, one for training the algorithm and one for estimating generalization performance. This is split is repeated where the split is systematically different in each repetition, called fold. Often ten repetitions are used, called ten-fold cross-validation. After the training of the algorithm the parameters that determine class distinctions have been set and the classifier can be applied to unseen data and will give a prediction of to which class that data belongs.

1.5 Communication

Many BCIs have been developed for communication, the most well-known of these is the visual speller, first developed by Farwell and Donchin (1988). In the standard visual speller a grid of characters or symbols is displayed on the screen, see Figure 1.1. These characters are highlighted per row or column. Subjects are asked to look at the character they want to select and count the number of times that character is highlighted. When the character the subject is looking at becomes highlighted there is P300 response in the brain, see Figure 1.1. By detecting this response in the brain and the unique order of highlights of each character or symbol, the visual speller is able to determine which character the subject is looking at. Since the first visual speller by Farwell and Donchin (1988) many improvements have been made to the visual speller. Improvements were made on the single trial detection by improving the machine learning techniques used (Thulasidas and Guan 2005, Martens and Leiva 2010, Martens et al. 2011). Different types of stimuli were used (Martens et al. 2009), and the timing of the stimuli were manipulated (Sellers et al. 2006, McFarland et al. 2011). Also the way of encoding the unique sequence of flashes for each character to improve the decoding speed or increase the tolerance to errors was investigated (Hill et al. 2008, Townsend et al. 2010). However, to achieve maximal performance all these visual spellers required the user to implicitly (or explicitly) foveate on the letter they wanted to communicate. What about the patients that no longer have the ability to direct their gaze? The importance of gaze-independent speller interfaces was re-emphasised by Treder and Blankertz (2010). They looked at the performance of a visual speller where subjects do not foveate the target (overt attention), but look at a fixed part of the screen and only pay their attention to the letter they want to select (covert attention). Improvements on the covert attention spellers were investigated by Treder and Blankertz (2010) and Treder et al. (2011). Spellers were also developed that used other modalities than the visual domain, i.e. auditory spellers (Höhne et al. 2010, Schreuder et al. 2010, Höhne et al. 2011, Schreuder et al. 2011, Hill and Schölkopf 2012), a tactile speller (Van Der Waal et al. 2011, Van Der Waal et al. 2012), and multimodal spellers (Belitski et al. 2011).

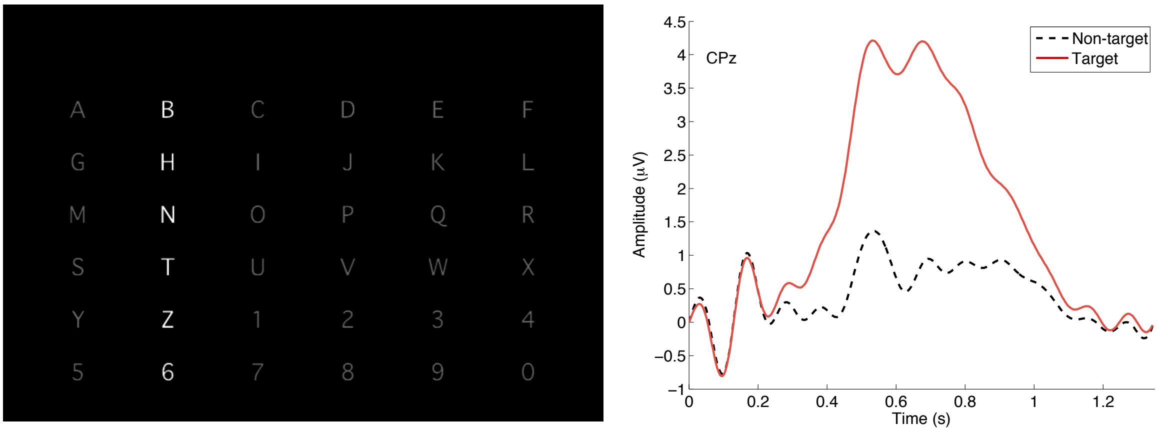

Figure 1.1: Examples of the visual stimuli for the visual speller (left) and the P300 response to a highlighted character of interest (right).

In the visual speller discussed above, communication is achieved by spelling out the message to be communicated letter by letter. Researchers are working towards a more natural way of communication by decoding concepts, words, or images directly from the brain (Simanova et al. 2010, Simanova et al. 2012, Huth et al. 2012). However, currently this still requires actual stimuli to be presented that are then decoded from the brain. In future, it may be possible to decode which word, concept or image someone has in mind. Moving towards this concept, it might be possible to decode words from the mind by using the semantic priming response. Semantic priming is a facilitation of response which occurs when responding to a word or picture when a related concept has been recently presented (Meyer and Schvaneveldt 1971). This facilitation has a distinct component in the brain response to a word or picture, as measured by the electroencephalogram. An unrelated word has a more negative going wave in central parietal regions around 400 ms after stimulus onset: the N400 response (Kutas and Hillyard 1984). Recently, it has been shown by van Vliet et al. (2010) that semantic priming also occurs when subjects prime themselves by keeping a word or concept in mind. Using this semantic priming response and a database of semantic word relations, it might be possible to determine with which word a subject primed him- or herself.

Communication at even higher levels is also possible. For example, Geuze et al. (2008) describe a technique, called chat-by-click, where instead of typing a message, a message is selected from a list of possible options. This selected message is then shown on the screen of the other user along with a list of possible responses. When the other user selects one of these responses, it is shown to first user and they see the selected response and a list of relevant possible response messages. The messages are stored in a database in the form of a conversation tree. When one of the users wants to send a message that is not in the list of available messages, it is possible to manually spell it. This message and the answer to it, are stored in the database for future use. In this way, the database grows dynamically with use. Chat-by-click can be seen as a coarse language model at the sentence level, which adapts to the user. Communication at the sentence level falls outside the scope of this thesis.

1.6 Outline

The main question I ask in this dissertation is: *How can communication using a brain computer interface be improved?* A starting point was to look at the currently prevalent system, the visual speller, and determine how it could be improved. The next step, was moving away from the visual speller and developing BCIs that meet requirements that the visual speller does not. First, late stage ALS patients of lose the ability to direct their eye-gaze, so a BCI was developed that could be used without eye-gaze. Next, a more natural way of communication was investigated by looking at how words or concepts could be communicated directly with a BCI.

A starting point for research on BCI for communication is to investigate what is already there and try to improve it. Therefore, chapter 2 looks at the visual speller as first defined by Farwell and Donchin (1988). Many improvements were already made over the years, so in this chapter a number of improvements were selected and the interaction of these was investigated. The following research questions about visual speller improvements were asked and answered: (i) *Does visual speller performance suffer from high stimulus rates?* (ii) *Does an increase in stimulus rate lead to a lower training time for an online visual speller?* (iii) *What aspect of the difference in the event related potential to a flash or a flip stimulus causes the increase in accuracy?* (iv) *Can an error-correcting (dense) stimulus code overcome the reduction in performance associated with decreasing target-to-target intervals?* When developing BCIs for patients, especially ALS patients, eye-gaze can be a problem. Some patients that would benefit from a BCI are not able to move or focus their eyes anymore. In chapter 3 the movement beyond the visual speller starts by transferring to another modality: the tactile modality. This chapter describes the development of the first tactile speller and answers the following questions: *(i) How well does the tactile speller perform?* (ii) *How does the tactile speller compare to the overt and covert visual speller and the covert Hex-o-Spell?* Up until now communication was achieved by spelling out a message character by character. Now we move further away from the visual speller by communicating concepts or words instead of single characters. Chapter 4 looks at the semantic priming response that occurs when observing words or concepts that are related. The question answered in that chapter is: *Is it possible to reliably detect semantic* *priming at the single-trial level?* Chapter 5 continues by describing the development of a BCI that makes use of the semantic relations between words to enable communication. The following questions are answered in this chapter: (i) *Is it possible to build a BCI based on semantic relations using an intelligent probe selection algorithm?* (ii) *Does applying a dynamic stopping technique contribute to the performance of this BCI?* (iii) *Does this intelligent selection contribute to the performance of the BCI?*, (iv) *Do the results of the BCI scale to large numbers of prime and probe words?* So, in chapters 2 and 3 the BCIs are based on communicating characters and the chapters are differentiated in which modality they use, i.e., visual and tactile respectively. Chapters 4 and 5 move to communication of concepts.

All chapters can be read individually. There is no preferred reading order. Chapter 4 and chapter 5 are closely related, but one can be read without reading the other. The glossary at the end of the thesis provides a description of the concepts, terms, and abbreviations used in this thesis.

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Chapter 2

Dense Codes at High Speeds

Abstract

This chapter investigates the effect of varying different stimulus properties on performance of the visual speller. Each of the different stimulus properties have been tested in previous literature and have a known effect on visual speller performance. This chapter investigates whether a combination of these types of stimuli can lead to a greater improvement. It describes an experiment aimed at answering the following questions: (i) Does visual speller performance suffer from high stimulus rates? (ii) Does an increase in stimulus rate lead to a lower training time for an online visual speller? (iii) What aspect of the difference in the event related potential to a flash or a flip stimulus causes the increase in accuracy? (iv) Can an error-correcting (dense) stimulus code overcome the reduction in performance associated with decreasing target-to-target intervals? We found that higher stimulus rates can improve the visual speller performance and can lead to less time required to train the system. We also found that a proper stimulus code can overcome the stronger response to rows and columns, but can not greatly improve speller performance.

2.1 Introduction

Brain-Computer Interfaces, or BCIs, allow someone to directly interact with a computer or electronic device without using the peripheral motor nervous system, by using only their brain signals. For example, someone could control a wheel chair, browse the internet, or spell out a sentence. This is achieved by having a user perform mental tasks with known brain responses. The brain signal is measured, e.g., using functional magnetic resonance imaging (fMRI), magnetoencephalogram (MEG), or electroencephalogram (EEG), while the user performs one of these tasks. The signal is then decoded and converted into commands that the computer or device can recognize. The interpretation is then communicated to the user. This process is called the BCI cycle, and is described in detail by van Gerven et al. (2009). There are a number of mental tasks that have a known, decodable, brain response. Slow Cortical Potentials (SCPs) can be elicited by training subjects for a long time and providing feedback on their performance. Over time they are able to learn to voluntary manipulate their brain activity in specific regions of the brain. This task has been successfully used in a BCI for communication by Birbaumer et al. (1999). Motor Imagery is another well researched mental task. Users imagine moving their left or right hand, or their feet. Each of these imagined movements give a distinctly localized response in the brain which can be used to drive a BCI (Blankertz, Dornhege, Krauledat, Müller, Kunzmann, Losch and Curio 2006, Scherer et al. 2007). A visual oddball task where the brain response evoked by a rare stimulus differs from the response to a common stimulus can be used to drive, for instance, a visual speller, which is also the topic of this chapter. Research is also conducted into developing new mental tasks that can be used to drive a BCI, e.g., subjective rhythmization (Vlek et al. 2011), and covert attention (Bahramisharif et al. 2010). This chapter will focus on the stimulation part of the BCI cycle and specifically on stimuli that can be used to drive a visual speller.

The visual speller, also called the P300-speller or matrix speller, was first developed by Farwell and Donchin (1988) and can be used effectively by more people than a motor imagery BCI (Guger et al. 2009). The visual speller implements a visual oddball paradigm by accentuating rows and columns of a letter grid in a random order. The accentuation is generally achieved by increasing the luminance of the stimuli. Users look at the character they want to select thereby determining which of the stimuli are the rare stimuli (the highlights of the target letter) and the common stimuli (the highlights of the non-target letters). Combining the response to rare and common stimuli with the knowledge of when each row or column was actually highlighted allows identification of the letter the user was looking at. The visual speller is mostly based on the P300 ERP component that is elicited by this oddball task. However, recent research shows that the early visual components (e.g., P1 and N2) also play an important role (Treder and Blankertz 2010). Much research has been done on the neural correlates of the P300 response and the influence of external factors (for comprehensive overviews, see Linden (2005) and Polich (2007)). Most visual speller BCI research to date has focussed on improving the detection of the P300 ERP component (Thulasidas and Guan 2005, Krusienski et al. 2006, Krusienski et al. 2008). However, there seems to be a recent trend towards stimuli that enhance the response properties (Fazel-Rezai and Abhari 2008, Hong et al. 2009, Martens et al. 2009, Salvaris and Sepulveda 2009).

An obvious way to increase the performance or speed of a visual speller would be to increase the rate at which the stimuli are presented to the user. This has been attempted before by McFarland et al. (2011), and they found that an increase in stimulus rate leads to a decrease in performance. However, they used the standard change in luminance to accentuate a letter. Martens et al. (2009) showed that by using a so called flip stimulus, a gray square behind each stimulus that rotates to accentuate it, there are less overlap and refractory effects than when using the standard luminance change. We expect that the lower overlap and refractory effects allow the stimulus rate to be increased without negatively affecting the performance or at least a diminished negative effect.

Another advantage for daily use of the visual speller would be shorter training times, i.e., the time required to gather enough examples to train a classifier. This time is now about ten minutes. Classifier performance after training improves with more training examples (Bishop 2006). We therefore expect that when increasing the stimulus rate, more examples are available in same time, requiring less subject training time to achieve the same performance level.

Regarding the lower overlap and refractory effects using a flip stimulus compared to a standard luminance change (flash stimulus), it is not clear which component, or components, of the brain response cause this difference. Since there is a difference in the visual stimuli presented on the screen we expect a difference in the early visual response components (P1, N2). However, the oddball paradigm has not changed, so we do not expect a difference in the later cognitive component (P3) (Linden 2005). As the visual speller uses both the early and late components, differences in these early components can influence the performance. At higher stimulus rates the overlap of responses to subsequent stimuli starts earlier, since the stimuli are closer together in time. Thus, a task relevant difference, i.e., a difference in response to rare (target) versus common (non-target) stimuli, in the early components instead of a late component would lead to a lower decrease in performance at higher stimulus rates.

New insights could be gained by looking at BCIs from an Information Theory perspective (MacKay 2003). Evoked response BCIs can be formalized as the problem of transmitting information over a noisy communication channel (Hill et al. 2008). In theory it is possible to communicate a single bit message with a single flash, but this is highly sensitive to errors. To be able to correct for errors, it is important to add redundancy to a message, e.g., by repeating it. This redundancy allows the message to be decoded even when the received message is partially corrupted. Information Theory concerns itself with how to do this in the best way. When the message is one of a fixed set, the most efficient way of encoding these messages is to maximize the Hamming distance.[1] The larger the Hamming distance, the more error correction is possible. When the decoder processes a code with a Hamming distance d, it is able to detect d-1 errors and is able to correct $d/2$ errors (MacKay 2003). When applying this to a visual speller, the letters are the messages that need to be sent. To encode these letters, a codeword is assigned to each letter. This codeword corresponds to the stream of accentuations in the visual speller. The noisy channel that is used for transmission is the brain and the measurement of its activity. Therefore, we expect that the noise of the measurements of brain response could be better corrected when using a code that has a larger Hamming distance than the standard row-column code.

[1] The Hamming distance is a measure of difference between two codes (MacKay 2003), determined by counting the number of bits that differ between two codes.

In order to empirically investigate these issues we performed an offline BCI experiment aimed at answering the following questions: (i) *Does visual speller performance suffer from high stimulus rates?* (ii) *Does an increase in stimulus rate lead to a lower training time for an online visual speller?* (iii) *What aspect of the difference in the event related potential to a flash or a flip stimulus causes the increase in accuracy?* (iv) *Can an error-correcting (dense) stimulus code overcome the reduction in performance associated with decreasing target-to-target intervals?*

2.1.1 Approach

The characters in the visual speller matrix can be manipulated in a number of ways to accentuate them and elicit the brain response of interest. The type of accentuation can be described by three main characteristics: (i) the way each individual character changes (the stimulus type), (ii) the speed at which they change (the stimulus rate), and (iii) the way changed characters are grouped (the stimulus pattern). We investigate two ways of changing the individual characters. First, we change the luminance of the character. This method has been used by Farwell and Donchin (1988), and is called a flash stimulus. Second, we overlay each character on a background rectangle and then rotate this rectangle 90 degrees to accentuate the character. This approach was first investigated by Martens et al. (2009) and is called a flip stimulus, an example of which can be seen in Figure 2.1. The advantage of the flip stimulus over the flash stimulus is that it has been shown to reduce overlap and refractory effects in the response to that stimulus (Martens et al. 2009).

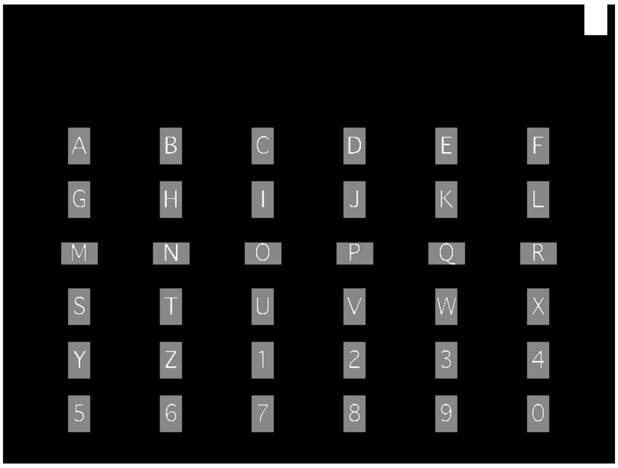

Figure 2.1: **Example of the flip stimulus:** The flip stimulus has a rectangle behind each character is rotated. Here, the third row is accentuated.

As mentioned earlier we also investigated the effect of varying the speed of change (stimulus rate).

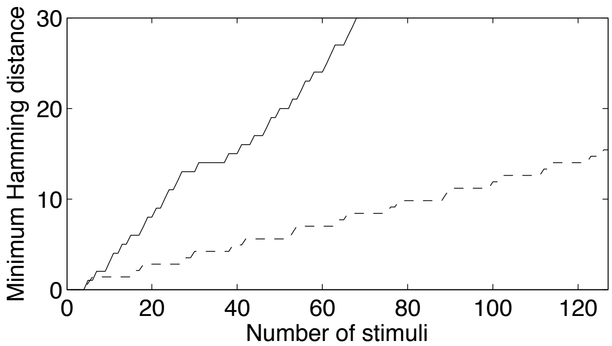

Figure 2.2: **Minimum Hamming distance:** The minimum Hamming distance versus number of stimulus events for the row-column pattern (dashed line) and the pseudo-random noise pattern (solid line).

The stimulus pattern, the grouping of the changing stimuli, was manipulated in two ways. First, the stimuli were changed in groups of rows and columns (RC), where first all columns were accentuated and then all rows. This is the same as in the original Farwell and Donchin (1988) speller. Second, the stimuli were all accentuated with a pseudo-random noise code (PRN) that was unique per letter. Here, we use a specific type of pseudo-random noise code called a golden code (Gold 2002). Golden codes are constructed in such a way that there is minimal correlation between pairs of codes and each code is only correlated with itself at time-point zero. These codes allow powerful error correction, due to the large minimum Hamming distance, see Figure 2.2. The codes are constructed according to the description given by Farquhar et al. (2008). A graphical representation of the stimulus patterns can be found in Figure 2.3. This also shows that the PRN codes have a much higher density (more active elements on the screen), which partly causes the higher minimum hamming distance. However, it also decreases the target-to-target interval (TTI)—the time between the accentuations of the target letter—leading to lower detectability of the targets (Gonsalvez and Polich 2002).

These three ways of manipulating the speller matrix can be combined. The main goal of this experiment is to determine whether a combination of these different ways of manipulation can lead to a greater improvement in visual speller performance.

2.2 Methods

2.2.1 Subjects

For this experiment 10 subjects were measured, six of whom were male. They were aged between 23 and 54 years old, with a mean age of 30 and a standard deviation of

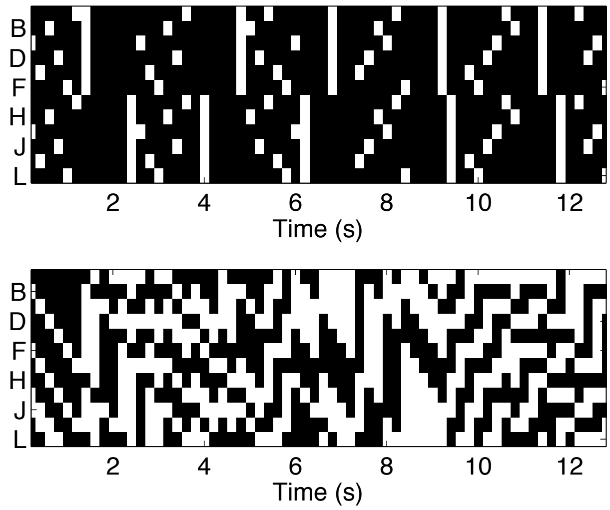

Figure 2.3: **Graphical representation of the stimulus patterns:** The row-column pattern (top) and pseudo-random noise pattern (bottom). Per character it shows for each point in time whether the character is in an accentuated (white) state or non-accentuated (black) state.

9. All subjects had normal or corrected to normal vision and were free of medication and without central nervous system abnormalities. The subjects participated voluntarily and were not paid for their contribution. One of the subjects was rejected due to subject reported fatigue issues. The subject was unable to focus attention on the stimuli towards the end of the experiment, which led to a confound in two conditions.

2.2.2 Stimuli

The stimuli of the experiment are based on a 6 by 6 character grid displayed on the screen, see Figure 2.1. As mentioned in the introduction, the accentuation of the characters in the grid was manipulated in three ways: (i) the way each individual character changes (the stimulus type), (ii) the speed at which they change (the stimulus rate), and (iii) the way they are grouped when changing (the stimulus pattern).

The two stimulus types consist of a flash stimulus, where the luminance of the stimulus was changed, and a flip stimulus, where accentuation was determined by a rotating rectangle behind each character. In order for the subject to still see all luminance changes as a flash, even when there are two flashes in a row, the highlight of a character consists of an ″on″ part of 75% of the stimulus duration and an ″off″ part of 25%. During the ″on″ part, the luminance is set to high (1.0), during the ″off″ part it is set at base level (0.3). For the flip stimulus, the stimulus onset asynchrony (SOA), i.e., the time between each rotation, is equal to the flash stimulus duration.

Stimuli were presented to the subject at stimulus rates of 5, 10, or 15 Hz, resulting in stimulus onset asynchronies (SOAs) of 200, 100, and 67 ms, respectively.

Two stimulus patterns were used: the standard row-column (RC) pattern where first all rows and then all columns are accentuated in random order, and the pseudo random noise (PRN) pattern, where each character is accentuated according to its own pseudo random noise code.

2.2.3 Equipment

The stimuli were presented with Psychtoolbox (`http://psychtoolbox.org/`) version 3.0.8 running in Matlab 7.4. The stimuli were displayed on a 17″ TFT screen, with a refresh rate of 60 Hz. The data was recorded using 64 sintered Ag/AgCl active electrodes using a Biosemi ActiveTwo AD-box and sampled at 2048 Hz. The EEG was recorded in an electrically shielded room. The participants used a foot pedal to indicate they wanted to start the next sequence.

2.2.4 Procedure

Per condition subjects were asked to look at and pay attention to a selection of 18 characters spread over the character grid (a, c, e, h, j, l, m, o, q, t, v, x, y, 1, 3, 6, 8, 0). The order of presentation was determined at random. The subject saw the character grid appear on the screen. For 3 seconds, a green circle would indicate to which character the subject was to attend. Next, the stimulus sequence would be presented, example stimulus sequences for both stimulus types can be found in Figure 2.3. After the stimulus sequence was presented, the subjects were asked to press a button to proceed with the next character.

Due to time limitations, not all combination of stimulus features were used in the experiment. It was decided to use the following conditions: RC5flash and RC5flip, to be able to compare the highlighting with rotation, RC10flip to determine the effect of speeding up the RC pattern, PRN5flip, PRN10flip, and PRN15flip to compare RC to PRN and determine the effect of speeding up the PRN pattern. These conditions were randomized in time over subjects.

2.2.5 Data analysis

The data was sliced into 600 ms pieces of data starting from the stimulus onset at time 0 ms.

Data analysis can be grouped into three separate steps: preprocessing, classification, and letter decoding.

The preprocessing consists of the following steps. First, eye artefacts were removed from the data by de-correlating the EEG data with data measured from EOG channels. (MacKay 2003). Next, linear trends were removed from the data. Then a common average reference (CAR) was computed and outlying letters and channels were removed. A channel was considered an outlier if its power differed by more than 3.5 standard deviations from the mean channel power. For letters this threshold was 3 standard deviations. To compensate for the removed channels another CAR was calculated, and any remaining outlying letters were also removed. The data was then bandpass filtered between 0.1 and 15 Hz. and down-sampled to 32 Hz.

The target and non-target classes were balanced before training the classifier, as there are more non-accentuations than accentuations. To prevent the classifier from always selecting the largest class (non-accentuation), a random sub-selection of that class was used to match the number in the smallest class. Next, the data was spatially whitened to equalize source powers. Finally, a linear classifier was trained on a binary problem (accentuated versus non-accentuated) using a L_2 regularized linear logistic regression algorithm (Bishop 2006). Leave-one-letter-out cross-validation was used to emulate an online setting as closely as possible. Separate classifiers were trained for each condition for each subject. For an overview of the input data used by the classifier, see Table 2.1.

In the letter decoding step, the per stimulus binary classifications were converted into 36-class letter classifications by selecting the letter where the individual decision values correlated highest with the stimulation code.

Table 2.1: **Number of single stimulus events used for training and testing the subject and condition specific classifiers:** The number of single stimulus events for the test set is the same for all subjects, the number of training examples was dependent on how many letters were rejected in the preprocessing steps. A single stimulus event consists of 600 ms of data with the start of the accentuation at 0 ms.

	Training set			Test set
Condition	Mean	Min	Max	
RC5flash	2030	1936	2057	121
RC5flip	1976	1815	2057	121
RC10flip	4060	3872	4114	242
PRN5flip	2117	2032	2159	127
PRN10flip	4092	3556	4318	254
PRN15flip	6308	5715	6477	381

2.3 Results

The binary target/non-target classification accuracy over subjects can be found in Figure 2.4. It shows that in all conditions subjects perform well above chance level (0.5). It also shows a clear difference between the row-column (RC) conditions (first 3) and the Pseudo-Random Noise (PRN) conditions (last 3), where the average binary accuracy of the PRN is lower than that of the RC conditions. A 2x2 repeated measures ANOVA was performed on the single epoch classification accuracy of four of the conditions, with factors pattern (RC vs. PRN) and stimulus rate (5Hz vs. 10Hz). It shows that for pattern the RC condition (M = 0.77, SD = 0.045) is significantly higher than the PRN (M = 0.68, SD = 0.031), $F(1,8) = 83.5$, $p < .001$, $\eta_p^2 = 0.91$. For stimulus rate the 5 Hz condition (M = 0.74, SD= 0.069) is significantly higher than the 10 Hz (M = 0.72, SD = 0.059), $F(1,8) = 9.33$, $p = .016$, $\eta_p^2 = 0.54$. There is no interaction effect, $F(1,8) = 1.52$, $p = 0.25$.

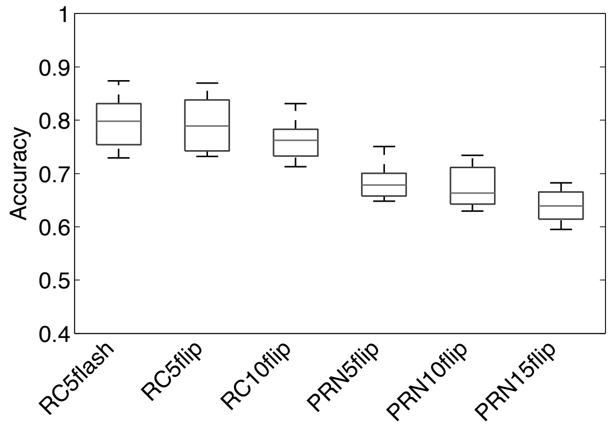

Figure 2.4: **Binary classification rates over subjects:** Chance level is at 0.5.

For a better speller performance comparison, the multi-class letter accuracy is shown in panel A of Figure 2.5. This accuracy is calculated by combining a number of binary classification decisions with the codebook to determine which letter was being selected. The integration time, i.e., the time over which binary decisions were collected before making a letter decision, is on the horizontal axis and classification accuracy on the vertical axis. This plot shows that the letter accuracy of all conditions is well above chance level (0.03). It also shows that the difference between the conditions is relatively small and the difference between the RC and PRN conditions that is present in the binary accuracy, is not present in the letter accuracy. A 2x2 repeated measures ANOVA was performed on the integration time in seconds required to reach a performance of 85%. The factors were pattern (RC vs. PRN) and stimulus rate (5Hz vs. 10Hz). There is a main effect of stimulus rate, where the 10 Hz condition (M = 11.6, SD = 4.04) is significantly higher than the 5 Hz (M = 6.98, SD = 3.31), F(1,8) = 61.3, p $<$ .001, η_p^2 = 0.88). There is no effect of pattern, F(1,8) = 0.033, p = .86, and no interaction, F(1,8) = 0.18, p = .69. A statistical analysis of the classification accuracy over multiple integration time measures was not possible due to a ceiling effect, also visible in panel A of Figure 2.5.

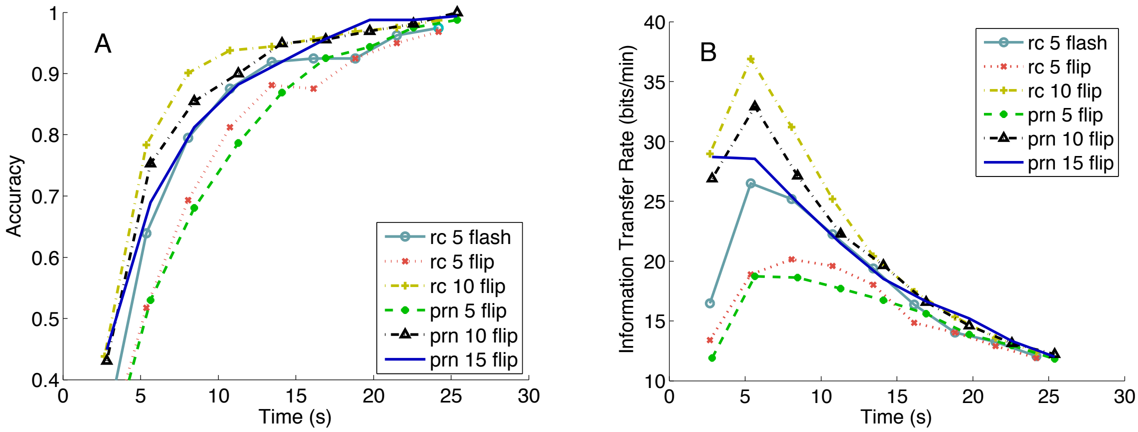

Figure 2.5: **Decoding performance:** Letter performance (A) and Information Transfer Rate (ITR) (B) per condition, averaged over all subjects. On the x-axis is the time the decoder has to collect binary decisions to combine them into a letter decision. Chance level is at 0.03

To facilitate comparison with other BCI systems, the Information Transfer Rate (ITR) was calculated for the letter accuracy. The following formula, as defined in (Wolpaw et al. 1998), was used to calculate the number of bits per decision:

$$B = log_2 N + P log_2 P + (1-P) log_2 \left(\frac{1-P}{N-1}\right) \tag{2.1}$$

The results can be found in panel B of Figure 2.5. These results show that the ITR peaks for most conditions at an integration time of about 6 seconds. It also shows that the RC10flip, the PRN10flip and the PRN15flip achieve the highest ITRs. The theoretical maximum ITRs (based on the single stimulus event accuracies) are 1.5 to 6.5 times larger than those in Figure 2.5 depending on the condition.

Figure 2.6 shows the letter accuracy for shorter training times for two different integration times (short and long). It shows that the conditions with higher stimulus rates require less time to train than the standard 5Hz conditions. It also shows there is a tradeoff between integration time and training time. When using a long integration time, the time required to train the classifier to get to a performance of 90% is shorter, but when using a short integration time, more training time is required to reach the same level.

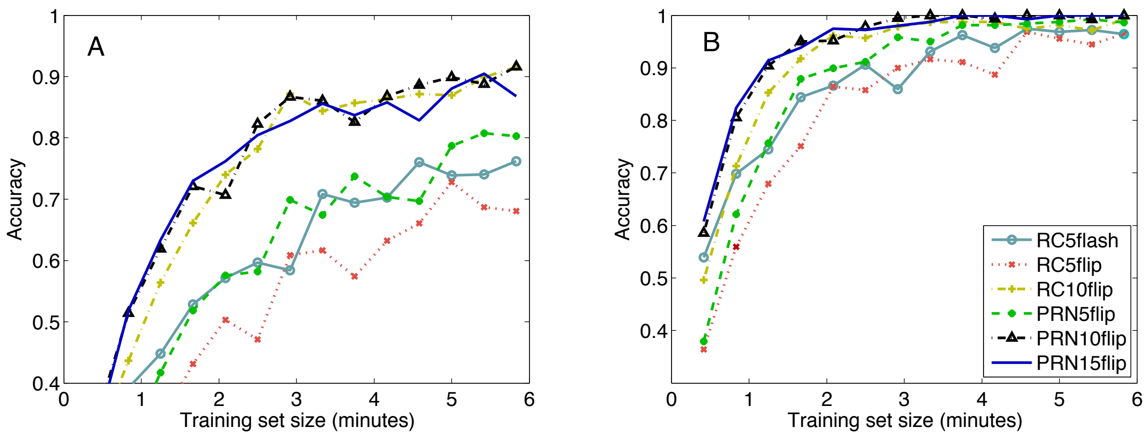

Figure 2.6: Decoding performance difference for smaller training set sizes: A: performance for an integration time of 8 seconds. B: Performance for an integration time of 25 seconds. On the x-axis is the amount of time in which examples were collected to train the binary classifier. Chance level is at 0.03

The difference ERPs for the grand average are shown in Figure 2.7. The lines in the plots are obtained by subtracting the grand average response to the non-target (common) stimuli from the grand average response of the target (rare) stimuli. The solid line represents the RC5flash condition and the dashed line represents the RC5flip condition. Note the difference in scaling between the occipital channels (PO7, PO8, and Oz) and the central channels (Cz and Pz). The colored boxes indicate statistical significant differences between the two conditions. The significance was determined using a cluster-based non-parametric statistical test, described by Maris and Oostenveld (2007). The colors indicate clusters identified by the cluster-based statistic. Topoplots showing the difference between the Flash and the Flip conditions are also shown. Here, asterisks indicate significant channels. Two clusters are displayed, the N2 cluster (180–281 ms) in blue and the P3 cluster (305–477 ms) in magenta.

These plots show that the primary visual response (P100 and N200) are slightly larger and occur earlier in the flip condition than in the flash condition. It also shows that the P300 response is slightly larger in the flash than in the flip condition.

A post-hoc analysis was performed to determine the effect of the above-mentioned differences between the flash and flip conditions (at a stimulus rate of 5Hz.) on the classification accuracy. The data was reclassified with the data being sliced in two ways, one to capture early responses (0-250 ms) and one to capture late responses (250-600 ms), by training two classifiers per condition, one for each time window. These classification results are presented in Figure 2.8. A two-factor repeated measures ANOVA with factors stimulus type (flash vs. flip) and slicing window (0-250 ms vs. 250-600 ms)

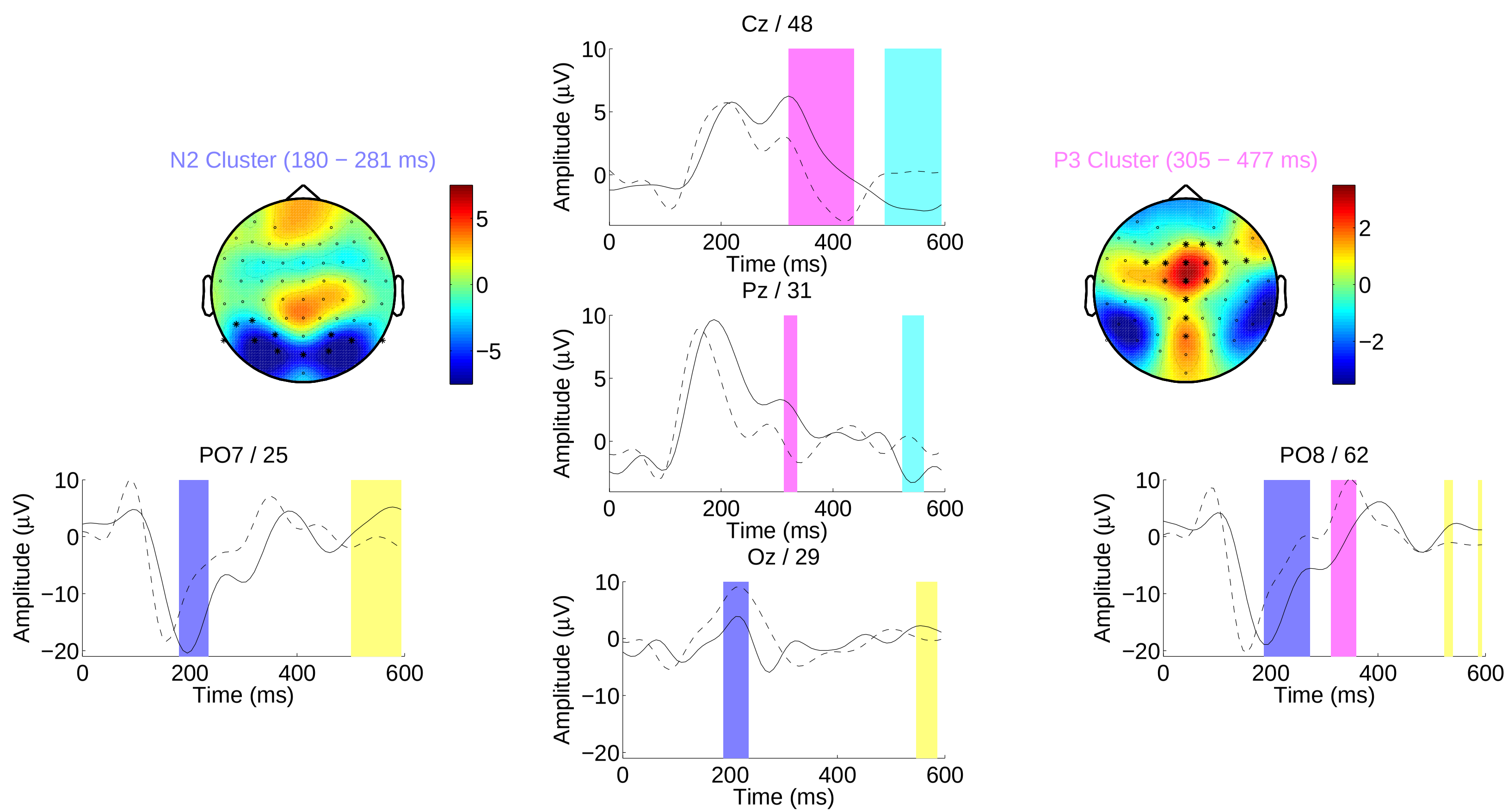

Figure 2.7: **Grand average difference ERPs:** For channels Cz, Pz PO7, Oz, and PO8. Lines represent the difference between target and non-target response (T - NT). The solid line represents the RC5flash condition and the dashed line represents the RC5flip condition. The marked colored areas indicates significant differences between the two conditions, as indicated by a cluster-based statistic. The color of each area indicates to which cluster it belongs. The topographic distribution for the N2 (blue) cluster (180–281ms) is shown on the left and for the P3 (magenta) cluster (305–477) is shown on the right. Asterisks indicate which channels have a significant difference in that time window.

was performed on this data. There was no effect of stimulus type, F(1,8) = 0.42, p = .54, a marginal effect of slicing window, F(1,8) = 4.51, p = .066, η_p^2 = 0.36, and a clear interaction effect, F(1,8) = 41.5, p $<$ .001, η_p^2 = 0.84. Further inspection of the interaction effect shows that in the early window there is a significant difference between flash (M = 0.65, SD = 0.051) and flip (M = 0.73, SD = 0.063), t(8) = 24.5, p = .001, η_p^2 = 0.75. There is also a difference between flash (M = 0.68, SD = 0.055) and flip (M = 0.62, SD = 0.028) in the late window, t(8) = 12.4, p = .008, η_p^2 = 0.61. There is a difference in slicing window for the flip stimulus, t(8) = 30.3, p = .001, η_p^2 = 0.79, but no difference in slicing windows for the flash stimulus, t(8) = 0.90, p = .37. The alpha level for the pairwise comparison was Bonferroni corrected to 0.0125.

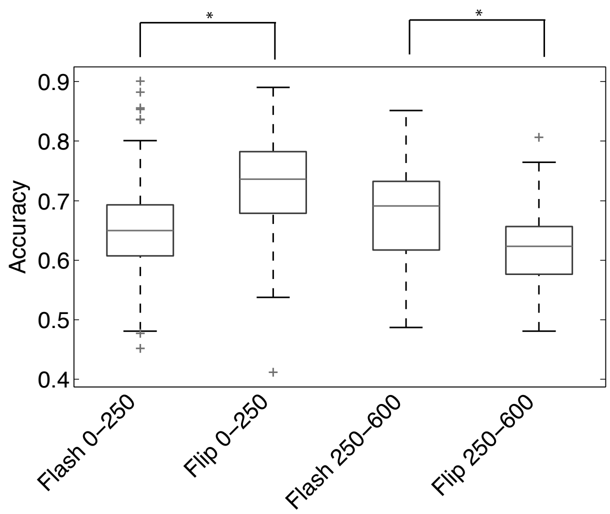

Figure 2.8: **Single event classification results:** Flash and Flip conditions with two slicing windows: early response (0-250 ms) and late response (250-600 ms). Chance level is at 0.5. * indicates a significant difference (p $<$ 0.0125).

2.4 Discussion

The results show that single event accuracy drops with increasing stimulus rate, while the letter accuracy increases with increasing stimulus rate. The results also show that higher stimulus rates result in less time required to train the classifier. However, a shorter training time requires more integration time during use. There is a significant difference in the ERPs when comparing flash with flip stimuli. These differences center around the N2 component in occipital channels and around the P3 component in central channels. These differences also affect the classification when slicing the data into two separate time windows. Last, the single event classification accuracy for the

PRN conditions is significantly lower than those for the RC conditions. This difference, however, is not present in the letter classification accuracy.

2.4.1 Accuracy

The differences in classification accuracy between low stimulus rates and high stimulus rates are influenced by two factors: information density during training time and during integration time (combination of single stimulus events into a letter decision). First, at higher stimulus rates there is more data for the classifier to be trained on (training examples). This influences the single stimulus event accuracy, which in turn influences the letter accuracy. Second, the higher stimulus rates result in more information for the letter decoder to base its decision on with the same integration time. This does not affect the single stimulus event accuracy, but only the letter accuracy. The results show that with higher stimulus rates, there is a decrease in the single stimulus event accuracy. This means that the increased number of examples during the training of the classifier cannot compensate for the reduced signature strength at higher stimulus rates. The results also show a slight increase in letter accuracy. Thus, the amount of extra information available during integration is able to overcome the reduced quality of the input signal.

We did a post-hoc re-analysis of the data where we kept the number of stimulus events constant instead of the time. Thus, the classifier uses the same number of stimulus events for all stimulus rates, during both training and integration. This resulted in an even larger decrease in single stimulus event accuracy with increased stimulus rate than we report above. This shows that the increased number of examples during classifier training for higher stimulus rates has a positive effect on the single stimulus event accuracy. The results also showed that there was still a small increase in letter accuracy with higher stimulus rates. Thus, the extra information available to the classifier during integration is able to overcome the reduced signature strength.

McFarland et al. (2011) also looked at the effect of stimulus rate on the visual speller. They found that the single stimulus event classification accuracy decreased with higher stimulus rates as well. However, they also found that the letter accuracy decreased with increasing stimulus rate. There are three differences between the experiment by McFarland et al. (2011) and our post-hoc analysis. First, the stimulus rates were not identical, but similar, 4 Hz and 8Hz versus 5Hz and 10Hz, respectively. Second, they employed a grid size of 8x9, where we use a 6x6 grid. The use of a larger grid increases the Target-to-Target interval (TTI), which leads to slightly increased accuracy for the same stimulus rate. Third, they used the checkerboard stimulus pattern (Townsend et al. 2010) in contrast to the row-column pattern used here. This last difference might cause the discrepancy in letter accuracy at higher stimulus rates. Sellers et al. (2006), have also looked at effects of stimulus rate, but they only looked at 5.7Hz and 2.9Hz.

They found that the lower the stimulus rate the higher the accuracy.

Thus, at higher stimulus rates there are more examples for the classifier to train on, increasing the single stimulus event accuracy, but not enough to overcome the decrease in signature strength. Also, at higher stimulus rates there is more information for the letter decoder to base its decision on, increasing the letter accuracy, which is able to overcome the decrease in signature strength, even without the use of extra stimulus events during classifier training.

2.4.2 Training time

Figure 2.6 shows there is a trade off between training time and integration time. When the classifier is able to train on more examples, i.e. the training time is longer, less integration time is required to achieve a fixed level of classification accuracy and vice versa. As a result, initial training of a visual speller BCI would take mere minutes. The first few minutes of use would take somewhat longer, as there is more integration time required. Guger et al. (2009) already showed that high speller performance can be achieved with a training time of five minutes. They used a RC type speller where 89% of subjects reach a letter accuracy of 80-100%. However, this is with an integration time of 29 seconds. Figure 2.6 shows that with an integration time of only 25 seconds, the average letter accuracy of all conditions is already well above 80% with 2.5 minutes of training time.

2.4.3 Flash vs. Flip

The electrophysiological difference between the flash and the flip stimulus, that is depicted in Figure 2.7, shows a significant difference in both the early visual response as well as in the later response. The difference in the later response is mostly in the P300 time range and sensor locations. The difference in the early visual response is restricted to the N200 component, which has traditionally been attributed to the detection of motion (Kuba and Kubová 1992). This response has also been used to drive an adaptation of the visual speller (Hong et al. 2009). There is also a non-significant difference in the P100-component, where the flip stimulus has a larger P1 component than the flash. The distribution of the classifier weights for the N2 and P3 clusters is almost identical to the ERP topography, showing that the classifier utilizes the differences shown in these ERPs. The classification results for the flash and flip in two different windows (0-250 ms and 250-600 ms), clearly shows the effect of the differences in the ERPs on the classification rate (Figure 2.8). It shows that the flip stimulus contains more class relevant information in the early window than the flash stimulus and that it contains less class relevant information in the late window than the flash stimulus.

Thus, when classifying on a 0-600 ms window of data, the classifier is mostly based on information in the 0-200 range in for the flip stimuli and mostly on the 250-600 ms range for flash stimuli. When increasing the stimulus rate, the early responses are affected last by overlap effects caused by incoming new stimuli. This explains why the flip stimulus is more robust at higher stimulus rates.

2.4.4 RC vs. PRN

The single event classification results (Figure 2.4) show a statistically significant difference between the row-column (RC) and pseudo-random noise (PRN) conditions, independent of stimulus rate. The RC pattern has a significantly higher single event performance than the PRN pattern. This is most likely caused by the higher density of the PRN pattern (6 elements per stimulus event for RC, and 18 for PRN), which leads to a lower TTI for the PRN pattern. (On average every second stimulus event, cf. every sixth stimulus event.)

However, the results also show that this lower accuracy is not observed for the letter decoding. In fact, the letter decoding accuracy is mostly better for the PRN conditions than for the RC conditions. As mentioned in the introduction, the PRN code was selected for the low correlation with other codes, resulting in a high minimum Hamming distance (see Figure 2.2). The increase in minimum Hamming distance between the RC pattern and the PRN pattern would allow the latter to be able to correct for more single event errors than the former. This is also reflected in the letter decoding accuracy and bitrates (see Figure 2.5), where we see that the PRN conditions have similar accuracy and bit rates as the RC conditions.

Thus, the PRN pattern has a lower single event accuracy due to the smaller TTI. However, the increased error-correction of the PRN code overcomes this disadvantage leading to similar or higher letter accuracies, compared to the RC pattern.

2.4.5 Conclusion

This chapter described an experiment aimed at answering the following questions: (i) Does visual speller performance suffer from high stimulus rates? (ii) Does an increase in stimulus rate lead to a lower training time for an online visual speller? (iii) What aspect of the difference in the event related potential to a flash or a flip stimulus causes the increase in accuracy? (iv) Can an error-correcting (dense) stimulus code overcome the reduction in performance associated with decreasing target-to-target intervals?

We are now able to answer these questions. (i) The single event accuracy of the visual speller suffers from higher stimulus rates, but the letter accuracy does not. (ii) The increase in stimulus rate indeed allows for less time required to train a classifier.

There also exists a trade-off between training time and integration time that holds at all stimulus rates. (iii) There are significant differences in the ERPs of the flash and the flip stimulus that affect the classification. There is more class relevant information in the early response for the flip stimuli than for the flash stimuli. In the late response this is reversed, making the flip stimulus more robust at higher stimulus rates. (iv) A well designed stimulus code is able to overcome adverse effects of decreased target-to-target intervals, but is not able to greatly increase the speller performance.

2.5 Future Work

Future work includes increasing the stimulus rate to even higher frequencies and the use of adaptive stimulus codes. Currently we use static stimulus codes that are fixed throughout the experiment. We also want to look at codes that are constructed during stimulation and are based on information available from the classification of previous stimulus events. We also want to exploit the trade-off between training and integration time. For instance, by developing a classifier that will keep adapting to the user by using data acquired during BCI use. This classifier would get better in time and lead to lower integration time required to reach the same accuracy level. However, to be able to keep adapting to the user, a way needs to be found to determine to which class the new incoming data belongs.

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Chapter 3

The Tactile Speller

Abstract

In the present study, a tactile speller was developed and compared with existing visual speller paradigms in terms of classification performance and elicited ERPs. The fingertips of healthy participants were stimulated with short mechanical taps while EEG activity was measured. The letters of the alphabet were allocated to different fingers and subjects could select one of the fingers by silently counting the number of taps on that finger. The offline and online performance of the tactile speller was compared to the overt and covert attention visual matrix speller and the covert attention Hex-o-Spell speller. For the tactile speller, binary target versus non-target classification accuracy was 67% on average. Classification and decoding accuracies of the tactile speller were lower than for the overt matrix speller, but higher than for the covert matrix speller, and similar to Hex-o-Spell. The average maximum information transfer rate of the tactile speller was 7.8 bits/minute (1.51 char/min), with the best subject reaching a bit-rate of 27 bits/minute (5.22 char/min). An increased amplitude of the P300 ERP component was found in response to attended stimuli versus unattended stimuli in all speller types. In addition, the tactile and overt matrix speller also used the N2 component for discriminating between targets and non-targets. Overall, this study shows that it is possible to use a tactile speller for communication. The tactile speller provides a useful alternative to the visual speller, especially for people whose eye gaze is impaired.

3.1 Introduction

For patients who suffer from severe paralysis as a result of diseases like ALS or spinal cord injury, brain-computer interfaces (BCIs) may constitute a way of communicating with the outside world. In general, a BCI records a physiological (e.g. electrophysiological or hemodynamic) signal from the user's brain and transforms the recorded signal into an output command. Output commands can range from the movement of a cursor on a computer screen to the control of a wheelchair (van Gerven et al. 2009).

A well-known BCI for communication purposes is the visual matrix speller (Figure 3.1a). First designed by Farwell and Donchin (1988), this speller consists of a letter matrix of which the rows and columns are intensified in random order. Users direct their attention to the letter they want to select. As a result, the event-related potentials (ERPs) elicited by the intensifications are different for attended (target) and unattended (non-target) letters. In particular, the amplitude of the P300 component of the ERP is generally found to be larger for attended letters than for unattended letters (Wolpaw et al. 2002). It has been found that the majority of healthy people can control the visual speller with high accuracy (Guger et al. 2009). In addition, severely disabled ALS patients have also been able to use the visual speller to communicate (Nijboer et al. 2008).

In most visual speller studies, subjects direct their eye gaze towards the letter they want to select. In contrast, it is also possible to use the visual speller by directing attention to the target letter while looking at a central point in the matrix. To distinguish these two ways of using the visual speller, we will speak of overt attention when eye gaze is directed towards the target letter, whereas we will speak of covert attention when eye gaze is directed at a central fixation point. The performance of the visual speller has been shown to decrease substantially when subjects are using covert instead of overt attention (Brunner et al. 2010, Treder and Blankertz 2010).

When the visual speller is used with covert attention, directing attention towards the target letter can be difficult, especially for targets farther away from the point of fixation. As a solution to this problem, Treder and Blankertz (2010) developed the Hex-o-Spell visual speller. This speller consists of six circles that all have the same distance to the point of fixation. (Figure 3.1b). The circles are intensified in random order while users direct their attention to one of the circles. In contrast to the matrix speller, selecting a letter consists of two steps. In the first step, the circle with the desired group of letters is selected. In the second step, the six letters are redistributed over the circles and the target letter is selected. The results of an experiment comparing Hex-o-Spell and matrix speller showed that when both spellers were used with overt attention, the Hex-o-Spell speller performed equally well as the matrix speller, but when both spellers were used with covert attention, Hex-o-Spell performed better (Treder and Blankertz 2010).

As such, these visual spellers rely to varying extent on intact voluntary eye gaze control. Unfortunately, in late stages of the disease, ALS patients sometimes lose the ability to control eye gaze. If this happens, the Hex-o-Spell seems a better option than the matrix speller. However, a number of patients lose their vision completely, and are therefore unable to use any type of visual speller.

For these patients, a speller that relies on information from another sensory modality might allow them to continue communicating with others. One option is to use the auditory modality. A number of auditory spellers have been developed. In these spellers, the rows and columns of the letter matrix are usually represented by different sounds, such as spoken numbers (Furdea et al. 2009) or environmental sounds (Klobassa et al. 2009) or by different spatial locations (Belitski et al. 2011, Schreuder et al. 2011). When presented with a stream of these auditory stimuli, subjects attend to the stimuli represent-

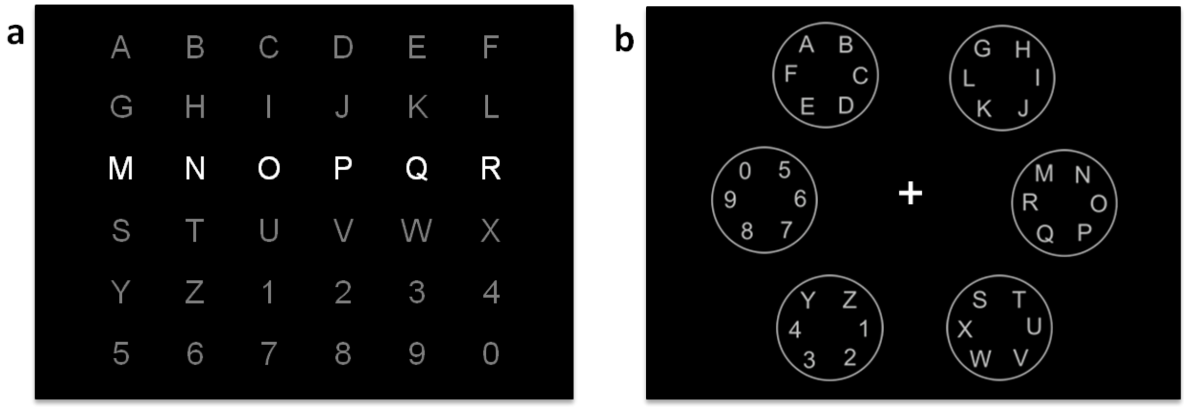

Figure 3.1: **Visual spellers:** a) matrix speller: rows and columns are intensified in random order; b) Hex-o-Spell: circles are intensified in random order.

ing the desired row and column. Performance of the auditory spellers was found to be lower than performance of the overt attention visual speller, but high enough for communication purposes.

The purpose of the present study is to investigate whether it would also be possible to build a speller based on tactile stimulation. An advantage of tactile stimulation is that it is relatively unobtrusive to others. Whereas the flashing rows and columns of the visual speller or the sounds of the auditory speller will be noticeable to other people, tactile stimuli can be presented privately to the user. Additionally, in contrast to visual and auditory spellers, a tactile speller does not prevent users from seeing and hearing the person with whom they are communicating. This advantage could also make a tactile speller attractive to patients who are not visually impaired.

BCIs based on somatosensory stimulation have been described previously. Müller-Putz et al. (2006) applied steady-state somatosensory stimuli of different frequencies to the left and right index fingers. Subjects directed their attention to one of the fingers, such that in the EEG, the stimulation frequency of this finger was stronger than the other frequency. In two subjects, it was possible to correctly identify which finger was attended in 70-80% of the cases.

In a separate study, Brouwer and van Erp (2010) presented short vibrotactile stimuli at different locations on the waist. Subjects counted the number of times a given target location was being stimulated while ignoring other locations. Subsequent analysis revealed an increased amplitude of the P300 component for evoked responses to stimuli at the target location. In addition, single-trial classification accuracies above chance level were obtained.

In the present study, a novel tactile speller interface was developed. Stimuli were applied to six fingers that represented the letters of the alphabet (Figure 3.2). Subjects were able to select letters by counting the number of stimuli on the corresponding finger. Figure 3.2 shows that, similarly to the Hex-o-Spell speller, selecting a letter is a two-step process. In the first step, a group of letters is selected, while in the second step, one letter from this group is selected.

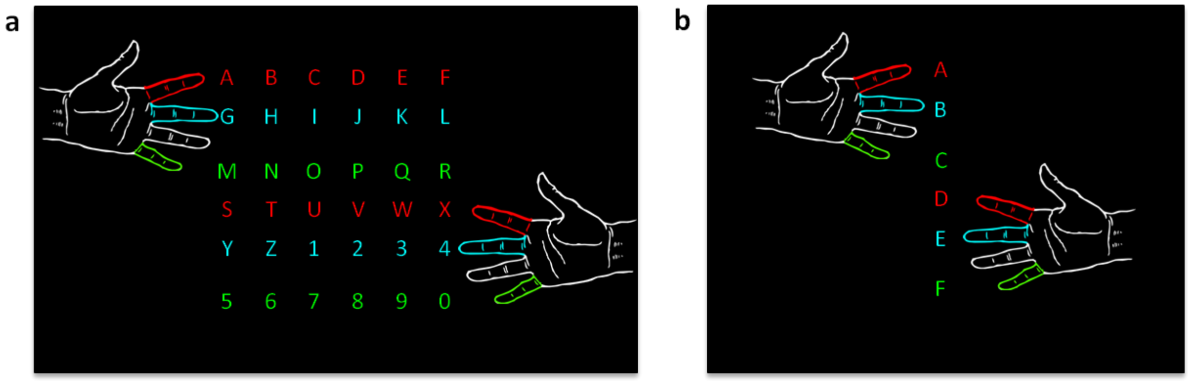

Figure 3.2: **The tactile speller:** Selecting a letter consists of two steps. a) Step 1: the fingers represent groups of letters. b) Step 2: the fingers represent the letters of the row that was selected in step 1.

The primary goal of this study was to assess the performance of the newly developed tactile speller. The second purpose of this study was to compare the new tactile speller with the overt and covert attention matrix spellers, as well as with the covert attention Hex-o-Spell speller in terms of spelling performance and underlying ERP features.

The online performance of a BCI is not necessarily the same as its offline performance, because of the online feedback. Online feedback may increase the speller's performance by increasing a subject's motivation, or it may degrade performance if the feedback is distracting. Therefore, we tested both the offline and online performance of the tactile speller. We hypothesized that there would be no difference between the offline and online performance of the tactile speller.

3.2 Methods

3.2.1 Participants

12 subjects (6 male), aged 19-54 (mean=27) years, participated in the experiment. One of them received course credits, while the others were volunteers. Four subjects had used the visual speller before and three of these subjects had also participated in other tactile BCI experiments. All other subjects were naive with regard to BCI experiments. Subjects did not have any neurological abnormalities, reported normal or

corrected to normal vision, and did not use medication. All subjects gave informed consent prior to the experiment. Due to excessive eye movements, one subject had to be excluded from the analyses.

3.2.2 Apparatus

EEG was recorded with 64 sintered Ag/AgCl active electrodes (BioSemi, Amsterdam), placed according to the international 10-20 system. This system uses a common mode sense (CMS) and a driven right leg (DRL) electrode instead of a ground electrode. The CMS and DRL electrodes were placed on the posterior part of the scalp. Additionally, 4 electrodes were used to record horizontal and vertical EOG. These were placed on the outer canthi of the eyes and below and above the left eye. The sampling rate of the EEG and EOG data was 2048 Hz. The BioSemi hardware does not apply any filters in the EEG frequency range.

Visual stimuli were presented on a 17” TFT screen with 800 x 600 pixel resolution and a refresh rate 60 Hz. Tactile stimuli were presented using piezoelectric Braille stimulators, built into two graspable devices (one for each hand), so that each fingertip rested on a separate Braille cell (Figure 3.3). One cell consists of two rows of four pins that can be pushed out of the cell over a distance of 0.7 mm with a force of approximately 0.7 N, which subjectively feels like a short tap on the finger. The stimulators were each placed inside a soundproof box to mask the sounds of the Braille cells accompanying the tactile stimuli. The stimulators were provided by the university’s electronic research group. The individual Braille cells were obtained from Metec AG, Stuttgard.

A risk of using these graspable tactile stimulators is that subjects might grasp one stimulator more strongly than the other. As a result, stimuli on different hands or fingers may not have the same intensity, which in turn might influence the performance of the tactile speller. Therefore, we measured EMG activity in each arm. EMG electrodes were placed on the elbow (lateral epicondyle of the humerus) as a reference and one on the m.flexor digitorum superficialis, an underarm muscle involved in grasping. Again, the CMS and DRL electrodes on the scalp are used instead of a ground electrode. The sampling rate was 2048 Hz.

Subjects were seated in front of a table. The screen was in the middle of the table at a distance of approximately 70 cm from the subject. The boxes with the tactile stimulators were placed 30 cm left and right of the body midline. Whenever subjects had to give responses, they used foot pedals to do so, in order to minimize movement of the arms and upper body.

Figure 3.3: Braille stimulator.

3.2.3 Conditions

The experiment consisted of four conditions, in which subjects used the matrix speller with overt attention, the matrix speller with covert attention, the Hex-o-Spell, and the tactile speller. In every condition, the goal was to copy-spell twelve random letters. In the visual conditions, the spellers were used offline. The tactile condition consisted of an offline and an online copy-spelling part. Each subject participated in all conditions, with the order of conditions randomized between subjects.

The difference between the two matrix speller conditions was that, in one condition, subjects used the speller with overt attention, whereas in the other condition they used covert attention. In the overt attention condition, subjects were allowed to fixate on the target letter, while in the covert attention condition, they were instructed to keep looking at the fixation cross and only direct attention at the target letter. The size of each character was 1.0x0.8 cm (0.82x0.65 $^\circ$ visual angle) and the entire matrix was 20x20 cm (16x16 $^\circ$ visual angle). Stimuli consisted of intensifications of the rows and columns in random order. Intensification was achieved by increasing the size of all characters in the row or column with a factor 1.5 for 100 ms.

The third condition was the Hex-o-Spell condition. Subjects were instructed to look at the fixation cross and only direct attention to the target. So, in this condition, covert attention was used. The Hex-o-Spell circles had a diameter of 4.2 cm (3.4 $^\circ$ visual angle) and the distance between the fixation cross and the center of each circle was 10.3 cm (8.4 ° visual angle). Stimuli consisted of the circles and the letters inside them increasing to 1.5 times their original size for 100 ms.

Finally, subjects used the tactile speller. Often, people need some time to get used to the tactile stimulation, and find the task of counting target stimuli more difficult and less intuitive than in the visual spellers. Therefore, the tactile condition started with a short practice block of six stimulation sequences. At the beginning of each sequence, subjects were instructed which finger was the target finger. When the subject pressed a foot pedal, the tactile stimulation began. After the stimulation subjects were asked how many taps they had felt, and three alternative answers were presented. Subjects selected one out of three choices with the foot pedal, and their response was followed by feedback ("correct" or "wrong"). In contrast to the main experiment, the number of target stimuli in a sequence was varied, so that the correct answer would not always be the same. At the end of the practice block, subjects were asked if they understood the task and whether they felt they could continue or needed more practice. One subject preferred to do the practice block a second time, while the others immediately continued with the experiment.

After the practice block, the tactile speller was first used offline and then online. The dataset collected during the offline block was used to train the classifier for the online block.

Tactile stimuli consisted of raising four pins of one Braille cell for 100 ms. Stimuli were applied to six fingers (index, middle and little finger of both hands). These fingers were chosen based on the results of a pilot study, which indicated that classification rates above chance level could be obtained when stimuli were applied to these six fingers. During tactile stimulation, only a fixation cross was shown on the screen.

Finally, when subjects had completed all four conditions, they were given the opportunity to use the online tactile speller to spell anything they liked. Although this was not compulsory, 8 subjects used this opportunity.

3.2.4 Trials

A trial is defined here as spelling one letter. All trials started with the speller being displayed on the screen, together with an instruction indicating which letter to select. When subjects were ready, they pressed a foot pedal to start the visual or tactile stimulation. For the matrix speller, one stimulation sequence lasted 36 seconds and consisted of 120 stimuli, 20 of which were target stimuli. The stimulus onset asynchrony (SOA) was 300 ms. Each sequence was built up of smaller subseries in which all fingers, circles, or rows and columns were stimulated once in random order, with the restriction that the unit that was stimulated last in one subseries could not be stimulated first in the next.

Thus, the same unit was never stimulated twice in a row.

As described in the introduction, in both the Hex-o-Spell and tactile speller, selecting one letter is a two-step procedure. Therefore, after the subject had pressed the foot pedal, there were two stimulation sequences, separated by a pause in which the subject could localize the new target. Each sequence lasted 18 seconds and consisted of 60 stimuli, 10 of which were target stimuli. The SOA was 300 ms. Note that selecting one letter involves the same number of stimuli and takes the same amount of time in all spellers.

Each stimulation sequence was followed by feedback on the screen, showing which letter or group of letters had been selected. In the offline conditions, the feedback always indicated that the character, circle or finger that was the target in the sequence had been selected. Thus, in these blocks, the feedback was not dependent on the subject's behaviour. Rather, it served to make the offline blocks as similar to the online block as possible. On four occasions throughout the tactile block, the feedback was replaced by the question how many taps were felt on the target finger. This was done in order to remind the subjects to keep counting target stimuli, because this task is less intuitive in the tactile condition.

In the online part of the tactile condition, the feedback depended on the ERP responses to the stimuli. At the end of each sequence, the classifier selected the finger that had the highest probability of being the target. The feedback on the screen showed that the letter or group of letters corresponding to this finger had been selected.

3.2.5 Signal Processing

The data was temporally down-sampled to 256 Hz using a moving average boxcar filter with 8 taps, and then decimated by a factor of 8. Subsequently, the data was sliced into sequences, each with a different target unit (i.e. the character, circle, or finger that was the target in the sequence). A sequence lasted 36 (matrix speller) or 18 (Hex-o-Spell and tactile speller) seconds. Linear detrending was applied to remove slow drifts in the signal and the data was re-referenced using a common average reference (CAR). Bad trials and bad channels (determined by an amplitude of > 3.5 times the standard deviation) were removed, followed by the calculation of a new CAR without the rejected channels and the removal of any remaining outlying trials. The data was spectrally filtered with a band-pass filter of 0.5-12 Hz and further down-sampled to 32 Hz, using a Fourier filter to prevent aliasing. Finally, the sequences were sliced into individual epochs from 0-600 ms following stimulus onset, and linear detrending was applied to the individual epochs.

3.2.6 Classification

Prior to classification, the number of target and non-target epochs was balanced by randomly selecting the same number of epochs from the non-target class as the number of epochs in the target class. In addition, the data was spatially whitened in order to remove cross correlation between channels. A linear classifier was then trained on a binary problem (target versus non-target stimuli) using an L_2 regularized linear logistic regression algorithm (Bishop 2006). Leave-one-sequence-out cross validation was used to find the optimal regularization settings.

The binary classification was followed by a decoding step. For each stimulation sequence the binary decision values were compared with the stimulation code. The stimulation unit (e.g. finger or Hex-o-Spell circle) that had the highest correlation between decision values and stimulus code was predicted to be the target unit in this sequence.

For the tactile and Hex-o-Spell spellers, one out of the six items was the target in each sequence. In contrast, for the matrix speller, each of the thirty-six units could have been the target. In order to make the results of the decoding procedure comparable, the 120 stimuli of one matrix stimulation sequence were divided in two sets, one containing 60 row intensifications and the other containing 60 column intensifications. In each of the subsets, it was determined which row (out of 6) or which column (out of 6) contained the target. Thus, for each of the spellers, the decoding procedure consisted of solving a six-class problem.

In addition, the information transfer rate or bit-rate of each speller type was computed as described by Wolpaw et al. (1998). The bit-rate of a BCI indicates how much information can be communicated per time unit. The bit-rate is dependent on classification accuracy, the number of classes, and the time it takes to make a classification.

3.2.7 Statistical Analyses

Two separate one-way repeated measures ANOVAs were used to compare the classification performance of the different speller types. Thus, in both ANOVAs, the independent factor was speller type, which had four levels: tactile, Hex-o-Spell, overt matrix, and covert matrix speller. In the first ANOVA, the dependent factor was the binary classification accuracy. In the second ANOVA, the dependent factor was the decoding accuracy at the end of the stimulation sequence, i.e. after 60 stimuli or 18 seconds. If an ANOVA yielded a significant result, pairwise comparisons were made comparing the tactile speller with the three visual spellers. The alpha level for these pairwise comparisons was Bonferroni corrected to 0.05/3=0.017. For these analyses the PASW Statistics 18.0 software package was used.

For all ERP analyses, the data was preprocessed as previously described. The only difference was that the data was down-sampled to 128 instead of 32 Hz, but using the same method. ERPs were baseline corrected relative to the 200 ms period prior to stimulus onset. Grand-average ERPs were obtained by averaging over epochs and subjects.

Cluster-based permutation tests (Maris and Oostenveld 2007) were used to assess differences between ERP waveforms. This nonparametric test finds clusters of electrodes and time points where ERP waveforms differ between conditions while controlling the false alarm rate. Two different permutation tests were performed. In the first test, for each condition the target and non-target ERPs were compared. Secondly, for the tactile offline and online conditions a difference waveform was computed by subtracting the non-target ERP from the target ERP, and these difference waveforms were compared to each other. Cluster-based permutation tests were performed with FieldTrip (Oostenveld et al. 2011).

The magnitude of the P300 amplitude difference between targets and non-targets was compared across the different speller types. For each speller type, the time window of significant P300 amplitude modulation was determined based on the results of the cluster-based randomization tests. More specifically, it was defined as the time window of the cluster of significant differences at Cz, around or closest to 300 ms. For each speller type, this time window is indicated with an asterisk in Figure 3.6a. For each subject, the area between the target and non-target ERP at Cz in the speller-specific time window was estimated using the trapezoid method and divided by the length of the time window. The P300 modulation was compared across the different speller types using a one-way repeated measures ANOVA followed by pairwise comparisons between the tactile and the three visual spellers.

3.2.8 Analysis of EMG data

EMG electrodes were placed on the lower arms in order to measure grasp strength during the tactile speller blocks. EMG data was down-sampled to 512 Hz using the moving average method described above and filtered with a band-pass filter of 22-250 Hz. Subsequently, the signal was rectified and low-pass filtered with a cutoff frequency of 15 Hz. In the following, we will use the term ipsilateral EMG to refer to EMG activity in the arm on the side where the target stimulus was presented and the term contralateral EMG to refer to EMG activity in the other arm. The following analyses were performed for the offline and online tactile speller blocks separately.

First, the EMG data was sliced into epochs of 0 to 600 ms after stimulus onset. For each epoch, the average ipsi- and contralateral EMG amplitude was computed. Amplitudes of all epochs were then averaged. A paired samples t-test was used to assess the difference between ipsi- and contralateral EMG amplitude.

In addition, the influence of EMG activity on the classification of EEG data was investigated. Using a median split, epochs were divided into a set with low ipsilateral EMG amplitude and a set with high ipsilateral EMG amplitude. EEG data of the high EMG set and low EMG set was classified separately, using the same binary classification algorithm as described above. The binary classification accuracies of the two sets were compared using a paired samples t-test.

3.3 Results

Unless otherwise indicated, tactile speller results are based on the offline block.

3.3.1 Classification

After the artefact rejection procedure, a similar number of trials remained in each condition. On average, classification was based on 225 to 240 epochs per class. The number of epochs per class determines the confidence interval around the chance level of the classification procedure (Müller-Putz et al. 2008). Given the number of epochs in this experiment, according to the binomial theorem, the 95% confidence interval of the chance level for the binary classification problem was 0.44 - 0.56. The confidence interval of the chance level for the 6-class decoding procedure was estimated using a random permutation procedure. For every subject and condition, the decision values were randomized and the decoding accuracy was computed 10,000 times. On average, the 95th percentile of the resulting distribution was at 0.30.

The results of the binary (target versus non-target) classification are shown in Figure 3.4a. It can be seen that classification performance exceeded the upper bound of the confidence interval, and therefore was significantly above chance level (0.5) for all spellers. Results of the repeated measures ANOVA indicated significant differences between the conditions ($F_{4,40}$=69.3, p<0.001, η_p^2=0.874). Pairwise comparisons showed that performance of the tactile speller (M=0.67, SD=0.046) was significantly lower than performance of the overt attention matrix speller (M=0.82, SD=0.053), p<0.001, d=-2.42, but higher than the covert attention matrix speller (M=0.58, SD=0.051), p<0.01, d=1.61. Classification performance of the tactile speller did not significantly differ from the Hex-o-Spell speller.

Figure 3.4b shows the results of the 6-class decoding procedure. At fixed moments throughout the stimulation sequence, all binary classifications up to that moment are combined to make a decoding decision concerning which unit of stimulation (e.g. finger or circle) is most likely to be the target in this sequence. The figure shows the accuracy of this decoding decision as a function of time. Performance exceeded the upper bound of

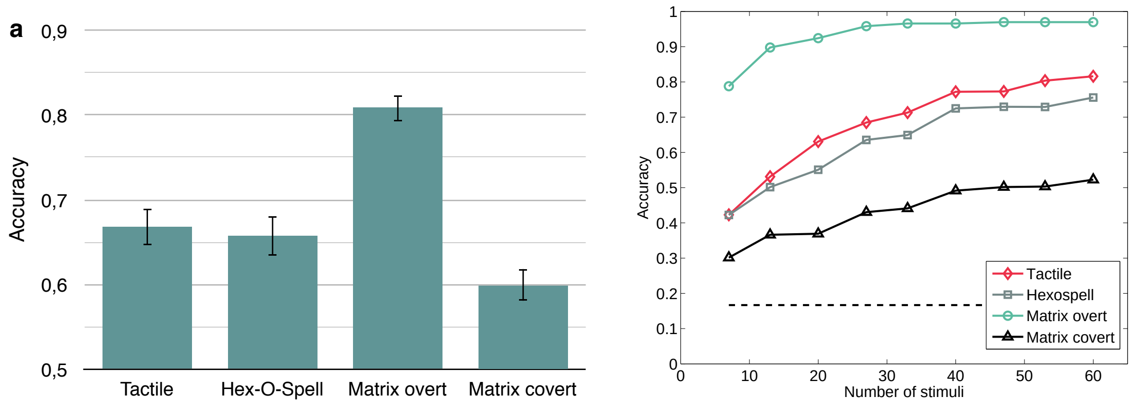

Figure 3.4: **Classification results:** (a) Binary (target vs. non-target) classification. Error bars show standard error of the mean. (b) 6-class decoding accuracy as a function of number of stimuli used for the decoding decision. The dashed line indicates chance level.

the confidence interval, and was therefore significantly above chance level (0.17) for all spellers. An ANOVA of the final sequence decoding results, i.e., after 60 stimuli, showed significant differences between the conditions ($F_{4,40}$=22.1, $p<0.001$, η_p^2=0.688). The pattern of decoding accuracies across spellers was similar to the pattern of classification accuracies. Performance of the tactile speller (M=0.82, SD=0.14) was significantly lower than performance of the overt attention matrix speller (M=0.97, SD=0.053), $p<0.025$, d=-1.24, but higher than the covert attention matrix speller (M=0.52, SD=0.20), $p<0.01$, d=1.54. Decoding accuracies of the Hex-o-Spell and tactile speller were not significantly different.

Classification accuracy in the tactile speller condition was similar for subjects with and without experience with tactile BCI experiments. On average, the binary classification performance of the speller was slightly lower for experienced subjects (M=0.63, SD=0.04) than for naive subjects (M=0.68, SD=0.05), but a t-test on the difference between the groups was not significant.

3.3.2 Information Transfer Rates

The information transfer rate or bit-rate of a BCI indicates how much information can be communicated per time unit. The bit-rates of the different speller types as a function of time can be seen in Figure 3.5. The average peak bit-rate of the tactile speller was 7.8 bits/minute. However, the best subject reached a bit-rate of 27 bits/min using the tactile speller, and had in fact a better classification performance when using the tactile than when using the overt matrix speller. This indicates that there are individual differences in how well people can use different speller types.

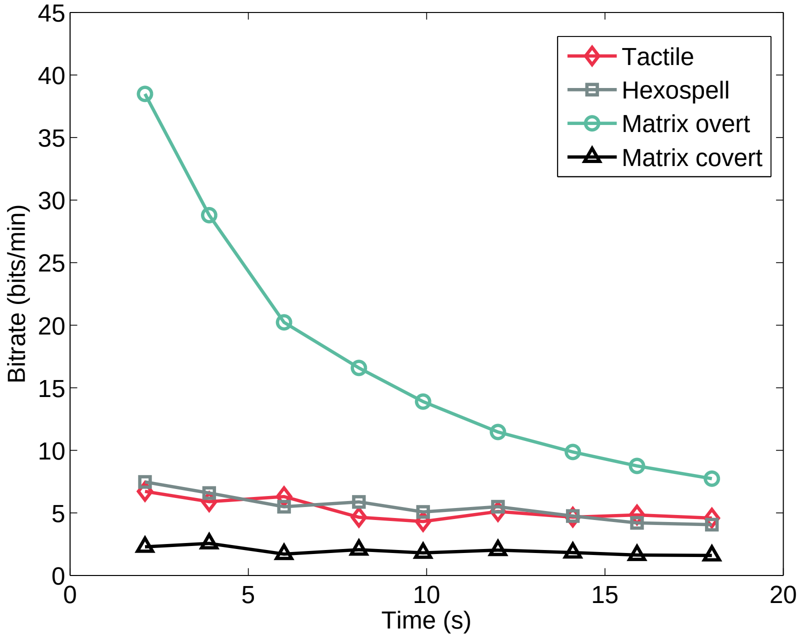

Figure 3.5: Information transfer rates: The amount of information that can be communicated with the different speller types as a function of stimulation time. As the time until making a classification (horizontal axis) increases, bit-rates decrease. Information transfer rate is highest for the overt matrix speller, lowest for the covert matrix speller and intermediate for the tactile and Hex-o-Spell spellers.

3.3.3 ERP results

For all speller types, the cluster-based permutation tests showed significant differences in P300 amplitude between target and non-target ERPs (Figure 3.6, panel a, b). This amplitude difference follows a typical P300 topography. The classifier weights indicate that for the tactile speller, the Hex-o-Spell and the overt matrix speller, the P300 difference is indeed of importance for classification (Figure 3.6c). Although the grand-average P300 difference between targets and non-targets was significant in the covert matrix speller condition, this difference was less useful for the classifier for this speller.

The difference in P300 amplitude between targets and non-targets at Cz was compared between conditions using a repeated measures ANOVA. The results indicated that the P300 modulation was indeed different across speller types ($F_{4,40}$=3.38, p=0.018, η_p^2=0.25). Subsequent pairwise comparisons of the tactile versus the three visual conditions showed that the P300 amplitude is modulated more strongly for the tactile than

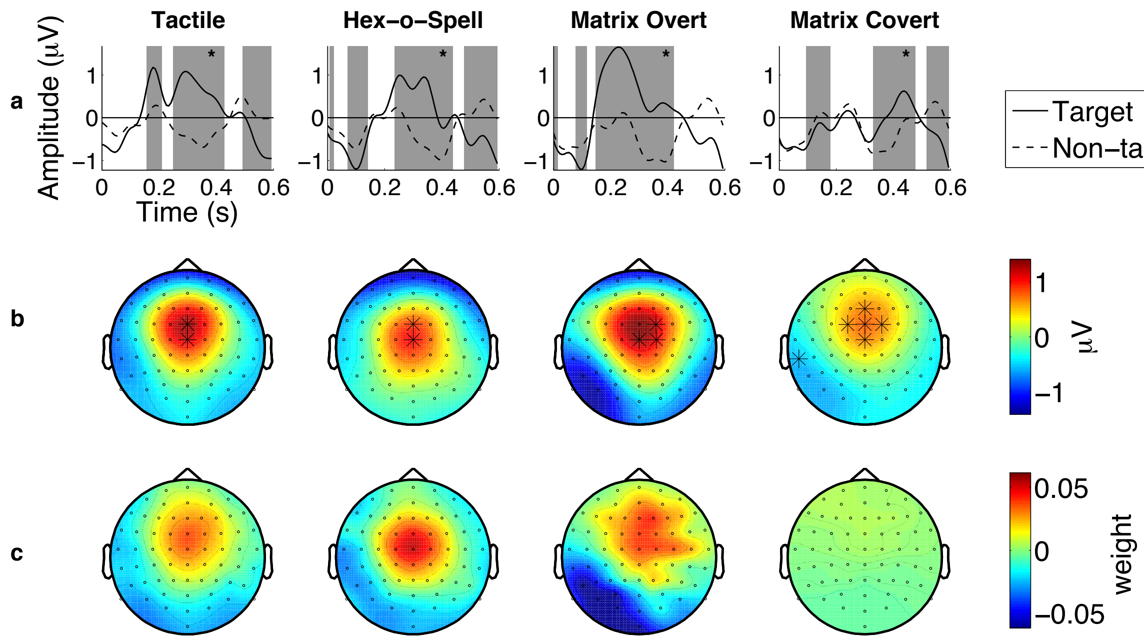

Figure 3.6: **P300 results:** (a) Grand-average target and non-target ERPs at Cz. The shaded areas indicate significant differences between the two ERPs. (b) Topoplots of the target–non-target difference in the time window of the cluster indicated by an asterisk in the plot in panel a. Asterisks in the topoplots indicate electrodes where the target–non-target difference is significant in this time window. (c) Topoplots of the classifier weights, averaged over subjects, in the time window of the significant P300 cluster.

for the covert matrix speller (p=0.013, d=0.91). No significant differences in P300 modulation were found for the tactile versus the overt matrix speller or the tactile versus the Hex-o-Spell speller.

In addition to the P300 component, the N2 amplitude also seemed informative for distinguishing between target and non-target stimuli in the tactile as well as the overt matrix speller. For the overt matrix speller, a significant N2 amplitude modulation was found over posterior electrodes (Figure 3.7, left hand side). The positive amplitude difference at central and frontal electrodes reflects the early stage of the P300 modulation. The classifier weights indicate that the posterior N2 difference is very informative for distinguishing target and non-target stimuli in the overt matrix speller, perhaps even more so than the P300 difference.

For the tactile speller condition, a significant N2 difference was also found (Figure 3.7, right hand side). However, this amplitude difference was located at electrodes over the somatosensory cortex. The negative amplitude difference at temporal electrodes was accompanied by a positive difference at frontal electrodes. In this case the

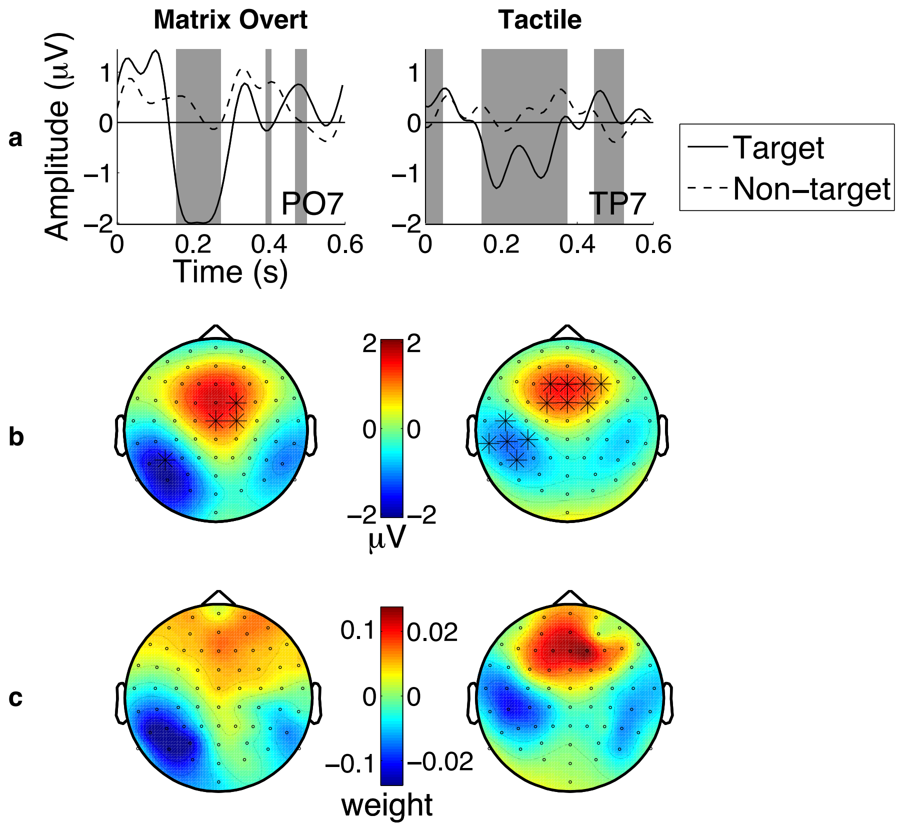

Figure 3.7: **N2 results:** (a) Grand-average target and non-target ERPs at PO7 (visual speller) and TP7 (tactile speller). The shaded areas indicate significant differences between the two ERPs. (b) Topoplots of the target–non-target difference in the time window from 150 to 250 ms post stimulus. Asterisks indicate electrodes where the target–non-target difference is significant in this time window. (c) Topoplots of the classifier weights in the time window from 150 to 250 ms. Scales on the left side of the color bars correspond to the plots on the left and scales on the right side of the color bars correspond to the plots on the right.

frontal difference most probably does not reflect P300 modulation, because in the tactile speller, the P300 modulation appears after the time window used for these topoplots. Rather, the temporal and frontal amplitude differences may reflect activity from the same source, as in the specified time window, the signals measured at electrodes TP7 (temporal) and AFz (frontal) are negatively correlated with r = -0.97 (for the visual speller, the correlation between PO7 and AFz is 0.24 in this time window). Figure 3.7c shows that both the temporal and frontal amplitude differences appear to be of importance for the classifier, though not as important as the N2 difference for the visual speller (note the difference in scaling between the visual and tactile plot).

For the Hex-o-Spell and covert attention matrix speller, no significant amplitude differences were found at any electrode in the 150-250 ms time window.

3.3.4 Online results of the tactile speller

The grand-average ERPs of the tactile speller were very similar in the offline and online parts of the experiment. The cluster-based permutation test on the target–non-target difference waveforms revealed no significant differences between offline and online speller (all cluster p-values >0.05).

Moreover, the online performance of the tactile speller did not differ significantly from its offline performance in terms of binary classification (online: M=0.66, SD=0.046) or 6-class decoding accuracy (online: M=0.79, SD=0.14). In addition to the online copy-spell block, 8 subjects decided to use the online tactile speller to write a word of their own choice. Five of these subjects were able to spell their desired word flawlessly, successfully correcting any errors if these occurred. The chosen words consisted of 3 to 8 letters and were written in 4 to 10 minutes.

3.3.5 EMG results

On average, EMG amplitude was larger on the side where the target stimulus was presented. In the offline block, ipsilateral EMG amplitude (M=26.10, SD=11.99) was significantly larger than contralateral amplitude (M=23.4, SD=11.4), t=3.41, p=0.007, d=1.03. In the online block, the difference between ipsilateral (M=27.8, SD=12.8) and contralateral (M=25.3, SD=11.8) EMG amplitude was not significant: t=1.92, p=0.084, d=0.58. Nevertheless, binary classification rates of EEG data did not differ between epochs with high ipsilateral EMG and epochs with low ipsilateral EMG. This was the case for both the offline (high EMG: M=0.63, SD=0.057; low EMG: M=0.66, SD=0.060) and online (high EMG: M=0.65, SD= 0.047; low EMG: M=0.64, SD=0.067) tactile speller blocks.

3.4 Discussion

The primary goal of this study was to develop a tactile speller. The results indicate that it is possible to build a speller based on selective attention to somatosensory stimuli on the fingertips. In addition, the classification performance of the newly developed tactile speller was compared with the performance of existing visual spellers. The performance of the tactile speller was lower than the overt matrix speller, higher than the covert matrix speller and similar to the Hex-o-Spell speller. This pattern was observed for the binary classification as well as the 6-class decoding problem.

Furthermore, the performance of the tactile speller was found to be sufficiently high for effective communication. The mean bit-rate of the tactile speller was 7.8 bits/min (1.51 char/min), and the maximum bit-rate observed in the best subject was 27 bits/min (5.22 char/min). This is low compared to bit-rates that are typically reported for (overt attention) visual spellers. However, it is higher than the bit-rates that were reported for auditory spellers, namely 1.54 bits/min in Furdea et al. (2009), 2 bits/min in Klobassa et al. (2009) and 5.26 bits/min in Schreuder et al. (2011). The bit-rate of the tactile speller is also higher than the bit-rate of the tactile BCI described in Brouwer and van Erp (2010), which was 3.71 bits/min. Finally, a more informal indication of the tactile speller's practical applicability is the fact that those subjects who decided to spell a word of their own choice succeeded in doing so. Together, the classification results suggest that, for patients with impaired eye gaze, the tactile speller could be a useful alternative for the visual speller.

In addition, a comparison was made between the ERPs that were elicited in the different speller types. The amplitude of the P300 component was significantly larger for target (attended) than non-target (unattended) stimuli in all speller types. This effect has been shown before for visual spellers (Farwell and Donchin 1988, Treder and Blankertz 2010) as well as for a tactile BCI (Brouwer and van Erp 2010). The size of the P300 amplitude modulation in the tactile speller was compared with the modulation in the other speller types. It was found that the P300 amplitude difference of the tactile speller was larger than the amplitude difference of the covert matrix speller, but not significantly different from the Hex-o-Spell or overt matrix speller. This might indicate that the task of counting target stimuli is more difficult with the covert matrix speller, as the amplitude of P300 generally becomes smaller when task difficulty increases (Kok 1997, Polich 2007).

Although this was not statistically tested, the latency of the P300 component appeared to differ across conditions. In particular, the latency seemed longer for the covert matrix speller than for the other speller types. In the covert matrix speller, stimuli are often presented in the visual periphery, where visual acuity is reduced (Westheimer 1965). As the latency of the P300 component is related to stimulus evaluation timing (Kok 1997, Polich 2007), an increased latency in the covert matrix speller might indicate that it takes longer to identify stimuli as targets or non-targets when using this type of speller.

In addition to modulations of the P300 component, significant modulations of the N2 component were found in the overt matrix speller and the tactile speller. For the overt matrix speller, modulation of the N2 component at posterior electrodes has been previously reported (Treder and Blankertz 2010). This effect may be caused in part by the fixation of eye gaze on the target. For the tactile speller, an N2 effect was found as well, but for this speller type the effect was found at electrodes located over the somatosensory cortex. It has been shown before that selective attention can enhance the amplitude of the tactile N2 (Michie 1984).

A significant difference in the grand-average ERPs does not necessarily mean that this difference is useful for classification. The difference between a target and non-target response should reliably occur at the single trial level in order to be of use to the classifier. In this study, the classifier weights indicated that the P300 component played a role in the classification procedure in the tactile, overt matrix and Hex-o-Spell speller. In addition, for the tactile and overt matrix spellers, the classifier made use of the N2 component as well. The N2 amplitude modulation seemed more informative for the overt matrix speller than for the tactile speller. Overall, the results show that neither the visual nor the tactile speller performance was exclusively based on the P300 component.

Analysis of EMG activity during tactile speller blocks indicated that on average, subjects had a slightly stronger grasp on the stimulator on the side where the target stimulus was presented. Nevertheless, this did not appear to influence classification performance. Therefore, we would expect similar performance of the tactile speller in subjects who are not able to use their arm muscles.

We could not verify directly whether subjects were indeed directing their eye gaze towards the target letter in the overt attention condition and towards the fixation cross in the covert attention conditions. However, the large difference in classification between overt and covert visual spellers indicates that this was the case. In addition, modulation of the N2 component of the visual evoked potential, assumed to result from fixation on the target letter, was found in the overt but not in the covert attention spellers. Moreover, it is more likely that subjects would use overt attention when they should use covert attention than vice versa. This would result in an overestimation of performance in the covert attention conditions. If the performance of the covert visual spellers were overestimated, the advantage of the tactile speller over the covert visual spellers would be even larger than reported here.

It is possible that changes in the stimulation paradigm could increase the performance of the tactile speller. In this experiment, we stimulated the index, middle and little fingers of each hand, while the hand was in a fist-like posture. Participants reported that it was sometimes difficult to distinguish taps on index and middle fingers of the same hand. Previous research indicates that the location of somatosensory stimuli is represented in the brain relative to an external, rather than a somatotopic, frame of reference (Azañón et al. 2010, Azañón and Soto-Faraco 2008, Kitazawa 2002). Accordingly, it was found that stimuli on adjacent fingers could be discriminated more easily if the distance between the fingers was larger (Riemer et al. 2010), and that interference between two tactile stimuli at fixed somatotopic locations was reduced if the stimuli were farther apart in external space (Soto-Faraco et al. 2004). However, interference in somatosensory signals has also been found to decrease when the stimulated areas are somatotopically farther apart, hence when stimulating non-adjacent fingers (Severens et al. 2010). This suggests that the performance of the tactile speller might be improved by stimulating fingers that are farther apart, for example thumb, middle finger and little finger, or by spreading the fingers during stimulation. In addition, stimulating distinct body parts might be better than only stimulating fingers.

Another possibility for further improvement might be to design a speller combining visual and tactile stimulation. Recently, a speller with concurrent auditory and visual stimuli has been developed (Belitski et al. 2011). The performance of the audiovisual speller was higher than the performance of the speller when stimulating in a single modality. In addition, it has been shown that there are strong cross-modal links between the visual and tactile modalities in spatial attention (Eimer et al. 2001, Macaluso and Maravita 2010, Spence et al. 2000). These results suggest that a tactile-visual speller might yield even better results than a speller with only tactile stimulation. However, possible performance benefits would come at the cost of an increased dependence on eye gaze.

As mentioned before, one of the reasons for developing alternatives for the visual matrix speller is because the visual speller does not work well for patients who suffer from a loss of eye gaze control. Previously, it has been shown that the Hex-o-Spell speller performs better than the matrix speller when subjects are not fixating on the target letter (Treder and Blankertz 2010). In the current experiment the performance of the tactile speller was similar to the performance of the Hex-o-Spell speller. Thus, for patients who are unable to control their eye gaze, the tactile speller seems a good alternative for the visual speller.

Moreover, the tactile speller does not need the visual modality at all, and can therefore also be used by patients who have lost their vision completely. In this study, we used the visual modality to inform users which finger represented which letter and which letter was selected at the end of each stimulation sequence. However, it is not necessary to present this information visually. For example, instructions and feedback could be given in the auditory modality. Furthermore, patients might learn the finger-to-letter associations by heart before they lose their vision, so that the letter matrix does not have to be presented before each trial. These adaptations were already successfully implemented in an auditory speller (Schreuder et al. 2011).

The tactile speller could also be a convenient option for patients who are not visually impaired. Since the tactile speller does not constantly require the visual or auditory modalities, users will be able to look at and listen to the person with whom they communicate.

In conclusion, the present study shows that it is possible to use a tactile speller for communication. The tactile speller might be especially useful for patients who cannot control their eye gaze, but also has advantages for people who are not visually impaired.

However, only healthy subjects participated in this experiment. Future studies with patients will have to show whether these findings generalize to the patient population.

3.4.1 Acknowledgements

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Chapter 4

Detecting Semantic Priming

Abstract

Semantic priming is usually studied by examining ERPs over many trials and subjects. This chapter aims at detecting semantic priming at the single-trial level. By using machine learning techniques it is possible to analyse and classify short traces of brain activity, which could, for example, be used to build a Brain Computer Interface (BCI). This chapter describes an experiment where subjects were presented with word pairs and asked to decide whether the words were related or not. A classifier was trained to determine whether the subjects judged words as related or unrelated based on one second of EEG data. The results show that the classifier accuracy when training per subject varies between 54% and 67%, and is significantly above chance level for all subjects (N = 12) and the accuracy when training over subjects varies between 51% and 63%, and is significantly above chance level for 11 subjects, pointing to a general effect.

4.1 Introduction

Semantic priming with written word pairs has been investigated since the first study by Meyer and Schvaneveldt (1971). In this first experiment subjects were asked to indicate whether pairs of strings were in the same or in a different category, where the categories were words and non-words. The first string in the pair is called the *prime* and the second is called the *probe*. When both prime and probe were words they could either be related or unrelated. The authors showed that there was a difference in response times and errors made when both strings were related words versus when they were unrelated words.

However, Meyer and Schvaneveldt (1971) only studied behavioral effects. Kutas and Hillyard (1984) published the first semantic priming experiment where they also investigated brain potentials. They studied the N400 ERP component, a negative going wave around 400 ms after word onset, in the response to sentence-final words. They presented sentences which ended in an expected word, a word related to the expected word, or a word unrelated to the expected word. The response to a word expected based on the sentence context resulted in the smallest N400 peak. Words that were unrelated to the expected word resulted in the largest N400 peak. Words that were related to the expected word showed a N400 peak amplitude that was between the expected and related word responses. Where Kutas and Hillyard (1984) showed this effect for words in a sentence, Rugg (1985) and Bentin et al. (1985) showed this effect also occurs with words in isolation.

A number of theories and models have been developed to explain this phenomenon, i.e., the spreading activation model (Collins and Loftus 1975), the compound-cue retrieval theory (Ratcliff and McKoon 1988), and the distributed memory model (Kawamoto 1988). The spreading activation model is based on the assumption that activation spreads from one node (the prime-word) to surrounding nodes (related words) which facilitates retrieval of related probes as their nodes are already activated. In the compound-cue retrieval theory, prime and probe are combined to form the compound cue, which is used to access memory. If the compounds are associated in memory it facilitates responses to the probe. The distributed memory model states that words are not single nodes, but consist of a distributed collection of nodes representing their characteristics. When some of these characteristics are activated by a related prime-word, it facilitates responses to probe-words. All three models have in common that they model the automatic process of lexical access. There is a long-standing debate on whether priming is only influenced by automatic processes (lexical access) or is also influenced by controlled processes (lexical integration) (Brown and Hagoort 1993, Kiefer 2002, Lau et al. 2009), and which of these processes is the basis of the N400 effect found in semantic priming studies. Although evidence has been gathered for both theories, there is no conclusive answer yet. Providing evidence for one of the above-mentioned theories falls outside the scope of this chapter.

The studies mentioned above only examine grand average ERPs, where for each condition several hundred examples are averaged, requiring hours of measurement time spread over multiple subjects. However, machine learning techniques (Bishop 2006) have successfully been applied to detect differences in brain responses between conditions at the single-trial level (Wolpaw et al. 2002), requiring just seconds to minutes of measurement time with a single subject. This means that, after a short training period, an algorithm is able to determine whether a short period of EEG data is the response to one condition or the other. The P300 brain component, elicited by an odd-ball paradigm is an example of an ERP that can be successfully detected at the single-trial level (Farwell and Donchin 1988, Geuze et al. 2012). A brain-computer interface (BCI) is an example of an application of single-trial level detection of ERP components. A BCI allows subjects or patients to control a device, usually a computer, based exclusively on brain activity (Wolpaw et al. 2002). The current chapter aims at determining whether similar success can be achieved by using the N400 component as elicited by a semantic priming experiment.

van Vliet et al. (2010) showed that semantic priming not only occurs when the subject is explicitly primed with a word or picture, but also when subjects prime themselves by thinking of a certain word or object. If subjects are able to prime themselves and it is possible to accurately detect priming on the single-trial level, it may be feasible to predict which concept a subject is thinking of.

In this work we want to answer the following basic question: *'Is it possible to reliably detect semantic priming at the single-trial level?'* Our hypothesis is that semantic priming is detectable at the single-trial level and that accuracy differs significantly from chance level. It is established that the N400 amplitude is correlated with the degree of association or relatedness (Kutas and Van Petten 1988). However, as this is a first study we chose to focus on distinguishing between strongly related and unrelated word pairs. The relatedness is determined by using the Leuven association database (De Deyne and Storms 2008). For the related word pairs we tried to select the word pairs with the highest association strength, without resorting to the use of synonyms.

4.2 Methods

4.2.1 Ethics Statement

The procedures used in the experiment were according the Declaration of Helsinki, and all subjects gave written informed consent. The procedures were approved by the Ethical Committee of the Faculty of Social Sciences at the Radboud University Nijmegen.

4.2.2 Subjects

Measurements were obtained from 12 native Dutch subjects, 7 of whom were female. They were aged between 22 and 33 with a mean of 26.75 ($\pm$ 3.08). All subjects had normal or corrected-to-normal vision and were free of medication and without central nervous system abnormalities. Subjects participated in the study voluntarily, signed an informed consent form, and did not receive a reward.

4.2.3 Stimuli

The stimuli consisted of two sets of Dutch word pairs: related and unrelated word pairs. The superset of related words was constructed by choosing 400 word pairs from the Leuven association dataset (De Deyne and Storms 2008). The Leuven association dataset was constructed by having subjects perform a continuous word association task.

The cues were constructed by the researchers, while the associated words were generated by the subjects. For each word pair their association strength was determined by dividing the number of times the response was given to that particular cue by the total number of responses to that cue. 400 pairs were selected for which the association strength exceeded 0.1, i.e., word pairs where that word was given in more than 10% of the responses.

The superset of unrelated words was constructed by combining 400 cue words from the Leuven association dataset with random word forms obtained from the Celex database (Baayen et al. 1995), making sure the random combination did not already occur in the Leuven association dataset.

Both sets were constructed in such a way that all 1600 words were unique. In the current experiment, the cues, constructed by the researchers of the Leuven dataset, were used as primes and the responses given by the subjects were used as probes.

To exclude confounding factors the stimuli in the two conditions were matched for word occurrence, number of letters and number of syllables. A matching program (Van Casteren and Davis 2007) was used to select 200 pairs from each of the two supersets in such a way that both primes and probes were matched for the confounding factors. The results of the matching are shown in Table 4.1. A number of example stimuli can be found in Table 4.2. A full list of stimuli can be found in Appendix A.

Property	Min	Max	Mean	STD
Unrelated				
Prime LogFreq	0	2.48	0.55	0.60
Probe LogFreq	0	2.76	0.78	0.61
Prime LettCnt	3	16	6.50	2.66
Probe LettCnt	3	12	5.94	1.99
Prime SylCnt	1	5	2.07	0.95
Probe SylCnt	1	4	1.82	0.76
Related				
Prime LogFreq	0	2.46	0.55	0.60
Probe LogFreq	0	2.63	0.72	0.62
Prime LettCnt	3	16	6.64	2.51
Probe LettCnt	3	12	6.45	2.22
Prime SylCnt	1	6	2.08	0.93
Probe SylCnt	1	4	1.95	0.77

Table 4.1: **Stimulus matching properties for the related and unrelated sets.** LogFreq: Logarithm of word frequency, LettCnt: Number of letters, SylCnt: Number of syllables.

Prime		Probe
	Unrelated	
tang (pliers)	-	opbrengst (yield)
berg (mountain)	-	drankje (small drink)
eland (moose)	-	eerbied (respect)
rog (ray)	-	maaier (mower)
gesp (buckle)	-	reflectie (reflection)
specht (woodpecker)	-	verpleger (male nurse)
	Related	
mier (ant)	-	klein (small)
tram (tram)	-	spoor (track)
racket (racket)	-	tennis (tennis)
naald (needle)	-	draad (thread)
inktvis (squid)	-	tentakel (tentacle)
slurf (trunk)	-	olifant (elephant)

Table 4.2: **Examples of stimuli used in the experiment.** Taken from the related and unrelated sets.

To validate the stimuli, a web survey was conducted in parallel with the EEG measurements, where subjects were asked to rate all word pairs on a 5-point relatedness scale from *not related* to *very strongly related*. 31 native Dutch subjects, 4 male, participated in the survey, aged between 17 and 61, with a mean of 24.4 ($\pm$ 9.9). Two subjects were rejected as outliers (more than 10% of the responses differed more than 3 standard deviations from the mean). The results of the survey can be found in Figure 4.1. Since the word pairs were selected to be either strongly related or not related at all, responses are predicted to be at the extremes of the scale. This is indeed the case, however there is some overlap in responses between the two sets. 13% of the responses do not correspond to the expected categorization. The unexpected categorization is not centered around a small amount of word pairs, but spread out over many, suggesting they are due to inter-subject variability in word knowledge and subjectivity in association rather than an error in the selection of the word pairs. 3% of the responses to unrelated pairs are labeled as related (strong relation and very strong relation), 7% of the responses to related pairs are labeled as unrelated (no relation and very weak relation). Another explanation for more related pairs being labeled as unrelated could be that, when subjects do not know the meaning of a word, they will label it as unrelated.

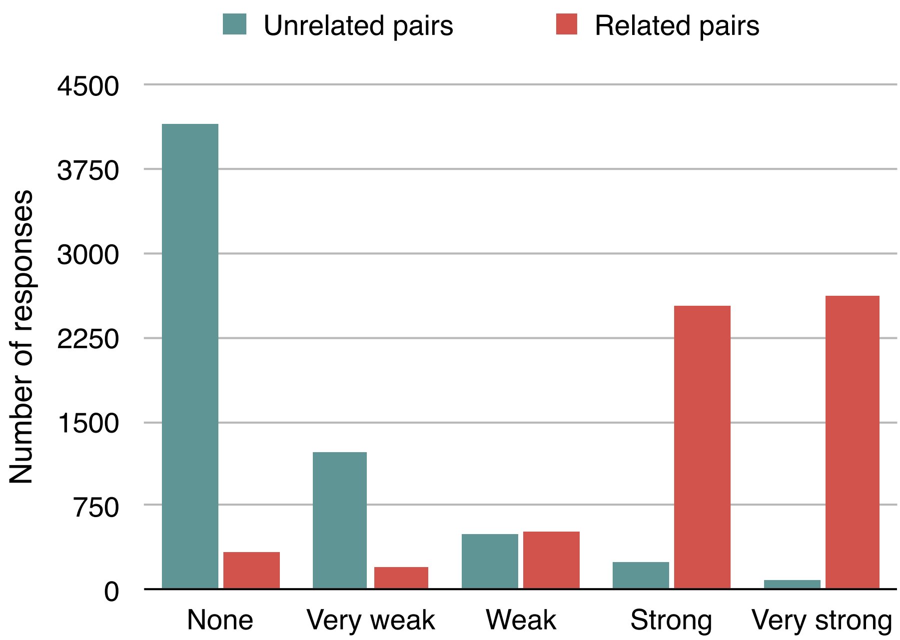

Figure 4.1: **Histogram of perceived relation between word pairs of both sets.** The 5-point scale on degree of relatedness is on the x-axis and the number of responses per pre-determined category, related (black) versus unrelated (red), is on the y-axis.

4.2.4 Procedure

Subjects were seated in a chair in front of a computer screen. After receiving the instructions, subjects first completed a short practice block in which they could familiarize with the task. The actual experiment is graphically represented in Figure 4.2. Subjects were presented with four blocks of about 15 minutes with a short pause between blocks. Each block consisted of twenty sequences, which in turn consisted of a baseline period of four seconds and five trials. One word pair was presented per trial. Subjects had to press a button to proceed from one sequence to the next. In each trial, first the prime was presented using a green colored font for 2000 ms. Next, a fixation cross appeared for 1500 ms, followed by the probe, presented in a white colored font. The probe was visible for 350 ms, followed by another fixation cross for 1500 ms. Subjects were instructed to pay attention to the words appearing on the screen and to determine whether the white probe-word was related to the green prime-word. To ensure subjects kept paying attention during the experiment, each block had 6 catch trials randomly distributed over the sequences. In a catch trial the subject was asked whether the last two words presented were related or not and they had to respond using two buttons. The word pair the subjects were asked about was always the last pair in a sequence.

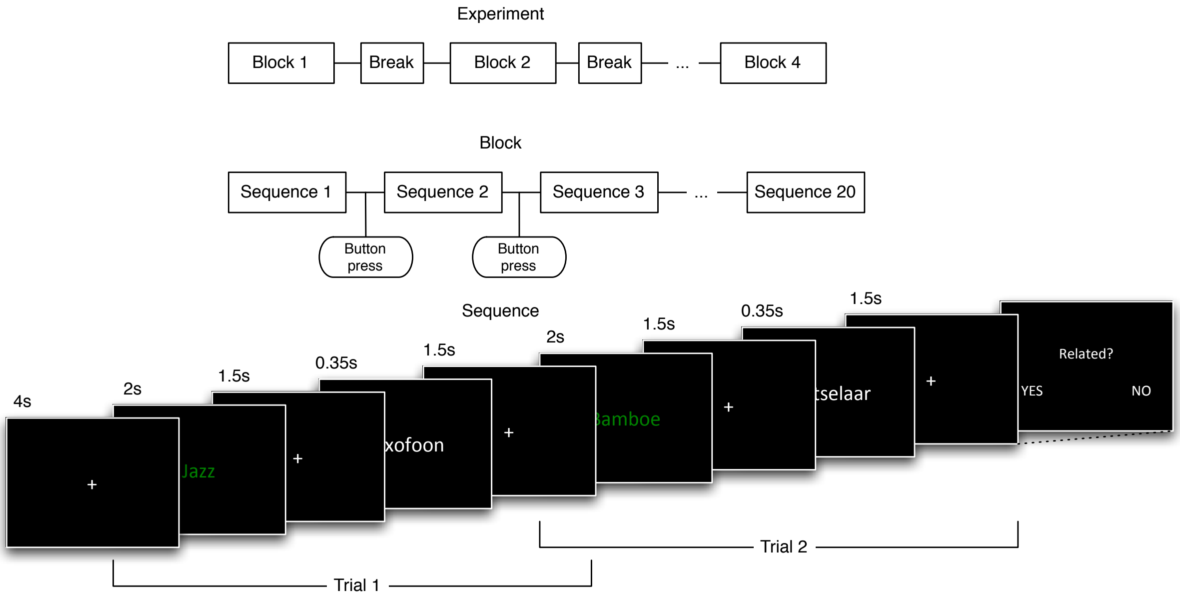

Figure 4.2: Schematic overview the experimental design. From global in time (top), to local in time (bottom).

4.2.5 Equipment

The stimuli were presented with Psychtoolbox (Kleiner et al. 2007, Brainard 1997, Pelli 1997) version 3.0.8 running in Matlab 7.4. The stimuli were displayed on a 17″ TFT screen, with a refresh rate of 60 Hz. The data was recorded using 64 sintered Ag/AgCl active electrodes using a Biosemi ActiveTwo AD-box and sampled at 2048 Hz. The electrodes were placed according to the 10/20 electrode system (Jasper 1958). The EEG was recorded in an electrically shielded room. The EEG offset for each channel was kept below 25 μV. A button box was used to allow participants to answer the catch trials and start the next sequence.

4.2.6 Data Analysis

All preprocessing was done using the Fieldtrip toolbox (Oostenveld et al. 2011). Two different pipelines were used in data analysis. One for the grand average ERP statistics and one for the single-trial classification.

For the grand average ERPs the data was sliced to the trial level, i.e. from prime onset to second fixation cross offset with 0 at probe onset (-3.5s – 1.85s). Next, the data was temporally down-sampled to 256 Hz. The data was detrended, a low-pass filter was applied at 30 Hz, and a linked-mastoid reference was computed. Relative baseline correction was applied using data from 100 ms before probe onset to probe onset. The preprocessing parameters were chosen to be able to compare them to other semantic priming experiments (Rugg 1985, Brown and Hagoort 1993, Kutas 1993, Lau et al. 2009). To test for significant differences between the two conditions the cluster-based non-parametric statistic described by Maris and Oostenveld (2007) was used. This test corrects for the multiple comparisons problem by incorporating a permutation test. For the statistical test the time of interest was set from 0 to 1000 ms after probe onset, and all 64 channels were used.

For the single-trial classification the data was again sliced to the trial level. It was detrended, bandpass filtered between 0.1 and 10 Hz and temporally down sampled to 32 Hz to reduce the number of features. Next, a linked-mastoid reference was computed. The time of interest was set from 0 to 1000 ms after probe onset, and all 64 channels were used, resulting in 2048 features (64 channels $\times$ 32 time points). The preprocessing parameters were chosen to allow comparison with other classification analyses of single-trial ERPs (Farquhar and Hill 2012). Classification was performed using an L_2 regularized logistic regression algorithm (Bishop 2006). The regularization parameter (C) that was used resulted from a simple grid search where the variance in all the data is used as an estimate of the scale of the data, which is then multiplied by [.001 .01 .1 1 10 100]. This range has been shown to result in a high performance (Farquhar and Hill 2012). Two classification procedures were performed. First, the classifier was trained for each subject, ten-fold cross-validation was applied where each fold consisted of 360 training epochs and 40 test epochs. The data was divided into ten equally sized blocks of sequential trials, each block was designated as validation set in one of the folds. Second, to determine the generalizability of the signal used by the classifier, leave one subject out cross-validation was applied. This resulted in 4400 training epochs and 400 test epochs, where all the tests epochs belong to a single subject. A binomial statistical test was used to determine whether classification accuracies differed significantly from chance level (50%).

In order to be able to compare the classification results with other studies the Information Transfer Rate (ITR) is calculated. This measure combines the accuracy, the number of classes and the time needed for a classification. Wolpaw et al. (1998) defined the ITR for a BCI as

$$B = V \cdot R \tag{4.1}$$

where B is the ITR in bits per second, V is the number of classifications per second and R is the amount of information gained per classification, where R depends on the accuracy and the number of classes. For details, see Wolpaw et al. (1998).

4.3 Results

4.3.1 Grand Average ERPs

The grand average ERP responses to the two conditions (related and unrelated word pairs) were calculated for each channel and each time point. A cluster-based non-parametric statistic (Maris and Oostenveld 2007) was used to determine whether the difference between the two conditions was significant. The significance-level was set to 0.01. The statistic returned one significant cluster between 330 and 600 milliseconds after probe onset. This cluster is mostly located centrally on the scalp, see the left panel of Figure 4.3, channels with more than 100 ms of significant different time-points are indicated with an asterisk. A representative channel was selected from these channels; channel CPz, which is shown in the right panel of Figure 4.3. It shows an enhanced (more negative) N400 response for unrelated probes compared to related probes. This difference remains to the end of the trial. However, it is no longer statistically significant outside the N400 window.

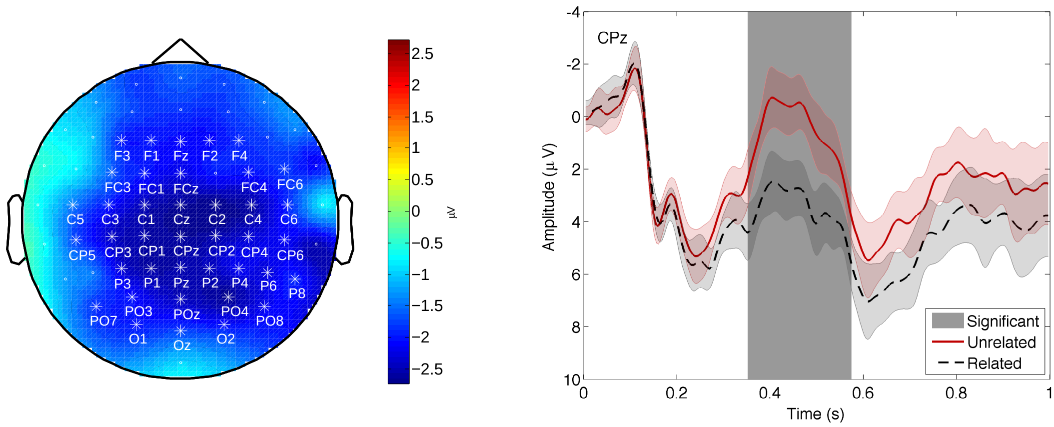

Figure 4.3: **Grand average results for the negative component.** Left panel: A topographic representation of the negative component between 330-600ms. The marked channels show a significant difference between related and unrelated probe responses. Right panel: ERP waveforms for channel Cz for related (black, dashed) and unrelated (red, solid). The area around each line represents the standard deviation, corrected for a within subject design (Field et al. 2012, p. 361–366). Channel Cz has been chosen as an example channel, as other significant channels are similar. Areas marked in grey show a significant difference.

4.3.2 Single-Trial Detection

The results of the classification can be found in Figure 4.4. The accuracies for the classifier trained on individual subjects can be seen on the left and the accuracies for the classifier trained over subjects can be seen on the right. The reported accuracies are mean accuracies of test set performance over ten folds.

When calculating the ITRs using Equation (4.1) with the time required to gather the data needed to make a classification (5.35 s), the mean ITR is 0.36 ± 0.29 (Maximum: 0.98) for the individually trained classifier and 0.16 ± 0.14 (Maximum: 0.53) for the classifier trained over subjects.

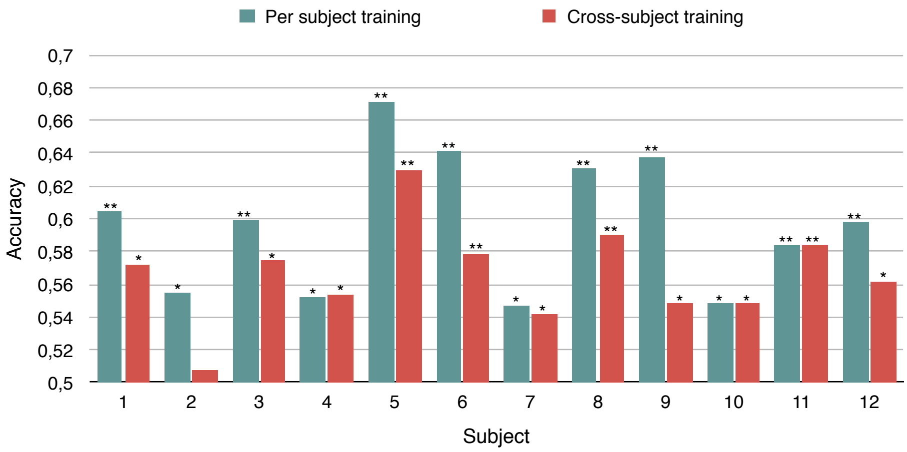

Figure 4.4: **Classification accuracies for the individually trained classifier and the classifier trained across subjects.** Accuracies are mean accuracies of test set performance over ten folds. (* $0.001 < p < 0.05$, ** $p < 0.001$).

4.4 Discussion

The results show one cluster around CPz where the response to related word pairs differs significantly from the response to unrelated word pairs; a central negative cluster. This cluster shows the typical N400 effect found earlier in semantic priming studies (Kutas and Hillyard 1984, Bentin et al. 1985, Rugg 1985, Brown and Hagoort 1993, Kiefer 2002, Lau et al. 2009). The late negative trend has also been found in earlier studies (Bentin et al. 1985, Brown and Hagoort 1993, Kutas 1993). The differences found in the responses between related and unrelated pairs are not caused by differences in word frequency, letter count or syllable counts, as the means were the same for both conditions for each of these possible confounds.

When training the classifier for each individual subject, the single-trial detection accuracies vary between 54% and 67%, where in all subjects the accuracy is significantly above chance level (50%). Even when training the classifier on data from other subjects, 11 out of 12 subjects show an accuracy significantly above chance level. This shows that the classifier is able to use a component in the subject's response that is the same over all subjects, pointing to a general effect.

There are a number of other ERP components which have also been studied at the single trial level: mainly the P300, Mismatch Negativity (MMN), and Error-Related Potential (ErrP). The P300 ERP can be divided into four conditions: (i) the overt visual P300, which has a detection accuracy of 77-85% (Geuze et al. 2012, Li et al. 2009, Li et al. 2012, Van Der Waal et al. 2012), (ii) the covert visual P300, which has a detection accuracy of around 58% (Van Der Waal et al. 2012), (iii) the tactile P300, with a detection accuracy of around 67% (Van Der Waal et al. 2012), and (iv) the auditory P300, with a detection accuracy of 65-74% (Höhne et al. 2012, Schreuder et al. 2010). The overt P300 results are higher than the other conditions, because there the subject foveates on the intended stimulus, leading to differences in the primary visual responses, which are also included in the classification, which means it is not detection of only the P300 component. The Mismatch Negativity has been detected with an accuracy of 69% (Tzovara et al. 2013), and the Error-Related Potential with an accuracy between 66-80% (Ferrez and Millán 2005, Dal Seno et al. 2010).

It has been established that the amplitude of the N400 response is correlated with the degree of relatedness between the prime and probe (Kutas and Van Petten 1988). In the current experiment the stimuli have been selected in such a way that the two categories the classifier needs to distinguish are as far apart as possible, i.e., the mean difference in relatedness of prime and probe is as large as possible. In a practical setting where such a constraint is not possible, we expect the detection accuracy to drop slightly, as the difference in amplitude of the N400 will be smaller in the situation where prime and probe are less strongly related. In future work, we will look at the effect of a lower degree of relatedness on the classification performance.

The significant classification results for the cross-subject classifier would allow the detection of semantic priming from the start of an experiment. Generally when using an online classifier it needs to be trained first. This is done by gathering data where one knows to which class each data segment belongs, i.e., a training block. A training block usually takes about ten to twenty minutes. However, when the classifier can be trained on data from previous subjects, new subjects can skip the training block. The classifier could later improve, i.e., adapt to an individual user, by retraining when subject data becomes available. However, the lower classification accuracy would mean that the performance is worse than when including a training block.

The ITRs achieved here are low compared to other word communication BCIs, such as the visual speller (Farwell and Donchin 1988). However, by relying only on the users' ability to identify associated concepts this approach offers the potential to detect a desired concept without the user having to know the correct word or even how spell it. This offers potential applications beyond simple communication, such as helping aphasics communicate the concept they are unable to say, or to help other users stuck in a 'tip-of-the-tongue' state.

Concluding, it is possible to detect semantic priming at the single-trial level, though the classification accuracies are low. The classification over subjects shows that there is a common response that is the same in all subjects and this response can be exploited for the detection of semantic priming.

When using the semantic priming response for BCI purposes using the timing parameters described here, it takes 5.35 seconds to present one probe. This could be reduced by using the timing parameters described by Brown and Hagoort (1993), reducing the time per probe to 3.94 seconds. Both these methods show one probe per target. If we show multiple probes for one target we could bring the time per probe down to about 1.5 seconds. This would increase the Information Transfer Rates reported in the results section. The ITR would increase from 0.36 ± 0.29 (Best: 0.98) to 1.3 ± 1.0 (Best: 3.5) for the individually trained classifier and from 0.16 ± 0.14 (Best: 0.53) to 0.57 ± 0.50 (Best: 1.9) for the classifier trained over subjects.

We have shown that it is possible to detect semantic priming at the single-trial level and that the single-trial accuracies differ significantly from chance level for all measured participants.

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Chapter 5

The Semantic Relations Speller

Abstract

This chapter investigates a possible Brain Computer Interface (BCI) based on semantic relations. The BCI determines which prime word a subject has in mind by presenting probe words using an intelligent algorithm. Subjects indicate when a presented probe word is related to the prime word by a single finger tap. The detection of the neural signal associated with this movement is used by the BCI to decode the prime word. The movement detector combined both the evoked (ERP) and induced (ERD) responses elicited with the movement. Single trial movement detection had an average accuracy of 67%. The decoding of the prime word had an average accuracy of 38% when using 100 probes and 150 possible targets, and 41% after applying a dynamic stopping criterium, reducing the average number of probes to 47. The chapter shows that the intelligent algorithm used to present the probe words has a significantly higher performance than a random selection of probes. Simulations demonstrate that the BCI also works with larger vocabulary sizes, and the performance scales logarithmically with vocabulary size.

5.1 Introduction

A Brain Computer Interface (BCI) (van Gerven et al. 2009) is a system that translates measured brain activity into machine commands without the use of any muscles or peripheral nerves. It could for instance allow someone to control a wheelchair or send commands to a computer. In theory this seems rather straightforward; a subject or patient performs a certain mental task and the computer tries to detect what the subject is doing. In practice, however, the signals are often measured outside the skull using, for instance, Electroencephalography (EEG) (Scherer et al. 2008, Wolpaw and McFarland 2004). Because of the electrical conductive properties of the dura, skull and scalp, the signal measured is a more indistinct and low dimensional version of the signal actually produced by the brain. Also, the signal produced by the brain is a coded signal, which needs to be decoded by the BCI system. The output of a BCI can be used for multiple purposes. Here, the focus is on communication.

A number of BCIs have already been developed with communication in mind. The best researched of these is the visual speller (Farwell and Donchin 1988). There the subject spells characters by looking at them on the screen. The letters are accentuated, often by a change in brightness, and subjects are asked to count the number of accents on the character they want to select. The accentuation of the target character elicits a P300 response (Polich 2007) in the subject's brain. This response is exploited by the BCI to decode the intention of the subject. However, visual spellers work best when subjects are still able to foveate the character they want to select, allowing the BCI to also use brain responses in the primary visual cortex. In the last few years, more research has been conducted into transforming the visual speller into a BCI that can also be used by patients that are not able to move or focus their eyes anymore. Treder and Blankertz (Treder and Blankertz 2010) looked at an alternative visual speller design, where foveation was not necessary. Other researchers have focussed on other modalities besides the visual modality, e.g., an auditory speller (Schreuder et al. 2011, Höhne et al. 2010), a speller where the auditory and visual modality are combined (Belitski et al. 2011), a tactile speller (Van Der Waal et al. 2012) and a speller based on imagined movement (Blankertz, Dornhege, Krauledat, Schröder, Williamson, Murray-Smith and Müller 2006).

However, all of these communication BCIs are based on spelling out the message to be communicated character by character. This chapter describes a communication BCI that is based on word selection by utilising semantic relations between words. By presenting many words in rapid succession and collecting responses to those words that are related to the word to be communicated (prime word), the BCI is able to decode this prime word. It builds upon earlier work, which shows that the semantic priming response, i.e., the response that differs when words are related versus unrelated, can be detected at the single trial level (Geuze et al. 2013). A first attempt at building this BCI utilised this semantic priming response. However, due to differences between the offline study in Geuze et al. (2013) and the online implementation, the single trial detection was reduced to chance level. These differences are explained in more detail in the discussion section. It was concluded that a more robust brain signal was necessary to operate the BCI. Actual movement was chosen for three reasons. First, actual movement provides a strong brain signal that can be classified with high accuracy. Second, when this BCI would be used by paralysed patients they would attempt movement. Blokland et al. (2013) has argued that the neural signal generated by attempted movement more closely resembles the neural signal generated by actual movement in non-paralysed subjects. Last, by having subjects press a button when they see a related word, more information about the actual brain activity is collected, than when only relying on semantic relations predicted from another source. To get an idea about the performance of this BCI using imagined movement, the best performing subject redid the experiment with imagined movement instead of actual movement.

The BCI works by presenting 100 probe words in rapid succession (one every 1.35

seconds). From the 150 possible prime words subjects select a word they want to communicate, and keep this word in mind. They press a button every time they are presented with a probe word that is related to their selected prime word. The probe words that are presented are a subset of the prime words that the BCI is able to detect, where it is possible that the same probe word is presented multiple times. The BCI collects the subjects EEG (electroencephalogram) data and uses a binary classifier to determine whether the brain's response to the probe word includes a movement response or not. By combining the classification results for each presented probe word with a database containing semantic relations between all prime and probe word combinations, the system attempts to identify the intended prime word.

In the study described here, there are 150 prime words and the same set of possible probe words. Randomly selecting a probe word to be presented next could suffice with such a small number of words. However, when using more possible words, this quickly becomes problematic. To solve this, an algorithm was developed that selects the probe word in an informed way. The algorithm uses the decoding state of the BCI and selects the probe word which, when presented, would elicit the most information in determining which word is the prime word.

The decoding and probe selection algorithms were implemented and the BCI was tested with 11 subjects in order to answer the following questions: (i) *Is it possible to build a BCI based on semantic relations using an intelligent probe selection algorithm?* (ii) *Does applying a dynamic stopping technique contribute to the performance of this BCI?* (iii) *Does this intelligent selection contribute to the performance of the BCI?*, (iv) *Do the results of the BCI scale to large numbers of prime and probe words?* Post-hoc simulations were used to answer the last two questions. The simulations were performed using the real subject single trial classification results. The collection of the data required to answer the first two questions took more than 2 hours per subject. Therefore it was decided to answer the last two questions with simulations.

5.2 Methods

5.2.1 Ethics Statement

The procedures used in the experiment were according the Declaration of Helsinki, and all subjects gave written informed consent. The procedures were approved by the Ethical Committee of the Faculty of Social Sciences at the Radboud University Nijmegen.

5.2.2 Subjects

The electroencephalogram (EEG) of 11 right-handed, native Dutch subjects was measured. Their age ranged from 18 to 28 (M=22.4, SD=3.2) and 7 of the subjects were female. All subjects had normal or corrected-to-normal vision and were free of medication and neurological abnormalities. All subjects participated voluntarily and gave written informed consent. All subjects but two (S1 and S5) received a reward in the form of money or study points. One participant (S1) also participated in a previous study (Geuze et al. 2013). One of the subjects (S2) was observed not to pay attention during the experiment and not perform the task and look around for periods of time. This was confirmed by the data, where the mismatch between expected button presses and actual button presses in the training block was more than 2 standard deviations higher than the average over subjects. On these grounds, this subject was not included in the analysis.

5.2.3 Procedure

The experiment consisted of five blocks. First, a practice block for the subjects to become acquainted with the task. Second, a training block where data are gathered to train the classifiers. Then, two test blocks where the classifiers are applied to the data and feedback is given about which word the subject saw as a prime. Last, there is a post-training block with the same properties as the training block, but shorter. This post-training block is used to determine any time-based deterioration of classifier performance due to non-stationarities in the data.

Subjects were seated in a comfortable chair in front of a computer screen. First the prime word was presented in a green colored font for 2000 ms. Then, a fixation cross was shown for 1150 ms, followed by a probe word for 350 ms and another fixation cross for 1150 ms, all in a white colored font. The probe and fixation cross were repeated until the total number of probes for the given prime word had been reached. A graphical representation can be seen in Figure 5.1. Subjects were instructed to press a button with their right index finger when they found that a probe word was related to the prime word they were shown earlier. They were instructed to keep their finger on the button throughout the experiment to minimize movement artefacts. Their EEG was measured during the experiment. The button press itself was not used during the online analysis, which were solely based on the recorded EEG activity.

In the training block 36 prime words are presented each followed by 5 related probes and 10 unrelated probes in random order. After presenting three prime word sequences consecutively, the subject can take a break. In a test block, 6 prime words are presented each with 100 probes. The probe selection is performed by the algorithm explained in detail in the decoding section below. Since the prime word sequence is too long to present at once (100 probes), subjects can take a break after 30 probes. After pressing a button to continue, the prime word is presented again to remind the subject. When all 100 probes have been presented feedback is given about which word the decoding algorithm selected based on the subject's brain activity. The feedback is given in a blue colored font. The post-training block is similar to the training block, only with 12 prime words instead of 36.

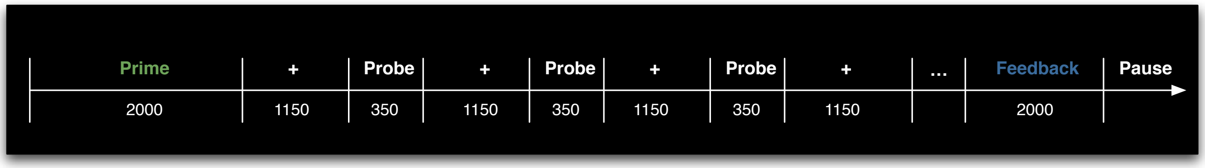


Figure 5.1: **Design:** Basic design of the experiment

5.2.4 Stimuli

Stimuli consisted of words drawn from the Leuven association dataset (De Deyne and Storms 2008). This dataset was constructed by having subjects perform a continuous word association task. The cues were constructed by the researchers, while the associated words were generated by the subjects. For each word pair their association strength was determined by dividing the number of times the response was given to that particular cue by the total number of responses to that cue.

For the training stimuli 36 prime words were selected. For each of these prime words, 15 probe words were matched, 5 which were related and 10 which were unrelated. For the related probe words, only words with a high association strength were chosen ($> .14$). For the unrelated words, words were selected with an association strength of 0. This resulted in 180 related probe words (M = 0.24, SD = 0.073) and 360 unrelated probe words (M = 0, SD = 0).

For the test stimuli a subset of the Leuven association dataset was constructed by selecting the 150 words with the most connections, i.e., number of related words. From this subset, 12 words were selected to be presented as primes. Three primes with a high number of connections (color, food, sea), three primes with a low number of connections (stick, tooth, child), and six random prime words (egg, tree, filth, boat, rose, rabbit). For the exact number of connections per prime word, see Figure 5.2. Seven of these words were seen as prime before, 6 in the training block (color, food, child, egg, tree, boat) and 1 in the practice block (sea). One of the prime words also occurred in the post-training block (tooth). For the probe words a selection from the constructed subset was used, for more information on probe selection see the decoding section below. The prime word could also occur as a probe word. Because this did not occur in the Leuven dataset, the association strength of a prime with itself was set to the maximum association value in the dataset. The average association strength of the probe words can be seen in Figure 5.3.

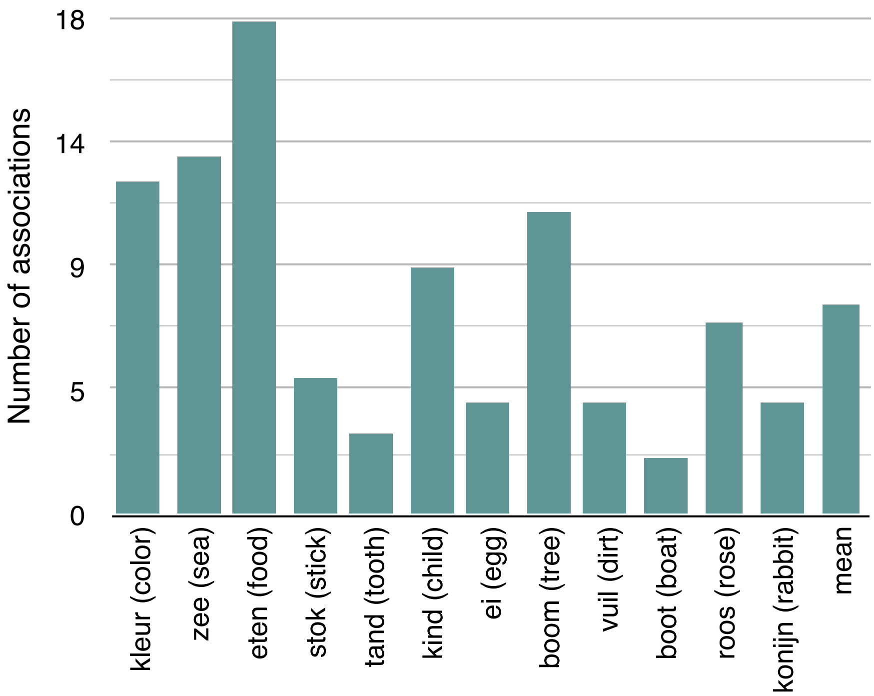


Figure 5.2: **Number of associations:** Number of associations for prime words in the test blocks.

The post-training stimuli were constructed in the same way as the training stimuli, but for only 12 prime words. This resulted in 60 related probe words (M = 0.21, SD = 0.078) and 120 unrelated probe words (M = 0, SD = 0).

An overview of all the stimuli can be found in Appendix B.

5.2.5 Equipment

The stimuli were presented with Psychtoolbox (Kleiner et al. 2007, Brainard 1997, Pelli 1997) version 3.0.8 running in Matlab 7.4. The stimuli were displayed on a 17" TFT screen, with a refresh rate of 60 Hz. The data were recorded using 64 sintered Ag/AgCl active electrodes using a Biosemi ActiveTwo AD-box and sampled at 2048 Hz. The electrodes were placed according to the 10/20 electrode system (Jasper 1958). The

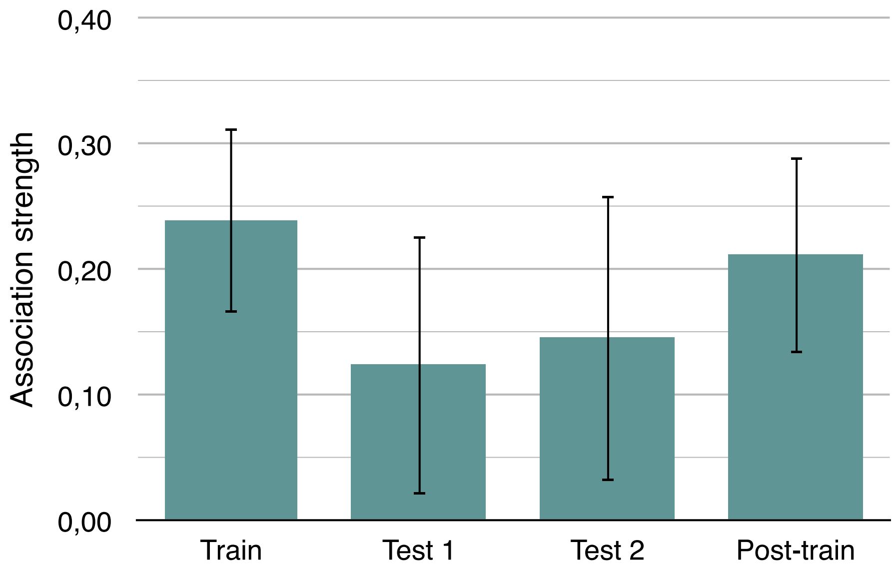


Figure 5.3: **Association strength:** Average association strength per block. The error bars indicate the standard deviation.

EEG was recorded in an electrically shielded room. The EEG offset for each channel was kept below 25 μV. A button box was used to allow participants to start the next sequence and indicate whether a probe word was related. Brainstream (`http://www.brainstream.nu/`), a toolbox for running online BCI experiments was used to coordinate the presentation of the stimuli, managing the EEG data and running the online classification analysis pipelines.

5.2.6 Data availability

The data is stored locally, in multiple locations, which are regularly backed-up. The anonymous data is available in on request from the lead author.

5.2.7 Data Analysis

The analyses were performed by Brainstream (`http://www.brainstream.nu/`), the plotting of the grand average results was performed using the Fieldtrip toolbox (Oostenveld et al. 2011).

A part of the analysis pipeline for both Event Related Potentials (ERP) and Time Frequency Representations (TFR) was common, therefore, these steps were performed on the continuous EEG data before they were sliced from 0–1350 ms after probe onset. This common pipeline first temporally down-samples to 256 Hz and removes linear trends. Bad channels were detected and removed and eye artefacts were removed by de-correlating the EEG and EOG channels. To maintain a consistent channel set the removed channels were reconstructed using spherical spline interpolation (Perrin et al. 1989). These data were then sliced and used as input for the two classification pipelines.

To classify the data based on the evoked single trial ERP, the training data were sliced from 0–1350 ms after probe onset. Outlying trials, i.e., a trial where the power differed by more than 3 standard deviations from the trial median, were removed. A common average rereference was calculated and the data were filtered between 0.1 Hz and 10 Hz. This was then used to train a binary L2 regularised logistic regression classifier. The related and unrelated classes were balanced by selecting a random subset from the unrelated class to match the number of trials in the related class. This was done to prevent the classifier from always selecting the dominant class. The above mentioned steps (except the outlier removal) were also performed per single trial in the online test blocks, after which the trained classifier was applied to the data, resulting in a decision value. The same preprocessing steps (except the balancing) were performed to obtain the data in the grand average ERPs. To test for significant differences between brain responses to related probes and to unrelated probes the cluster-based non-parametric statistic described by Maris and Oostenveld (2007) was used. This test corrects for the multiple comparisons problem by incorporating a permutation test.

To classify the data based on the induced response a single trial time frequency representation was used. The training data were sliced by brainstream from 0 – 1350 ms after probe onset. Outlying trials were removed, after which a rereference based on surface laplacian was applied to increase spatial specificity. The time frequency representation was calculated with a hanning window of 500 ms with an overlap of 50%. Then the frequencies of interest were selected (8-24 Hz) and the resulting data were used to train another binary L2 regularized logistic regression classifier. The related and unrelated classes were balanced by selecting a random subset from the unrelated class to match the number of trials in the related class. The above mentioned steps, excepting the outlier removal, were performed on the online single trials in the test blocks, before applying the trained classifier.As before, the data that were used to train the classifier was also used to plot the grand average TFRs. To test for significant differences between the conditions the cluster-based non-parametric statistic was used with the same settings as for the ERP analysis.

A combined classifier was obtained by adding the decision values of the individual classifiers. The classifiers are calibrated to produce valid estimates of the likelihood of a button press given the features. Thus, adding decision values in this was is equivalent to a bayesian information combination under the assumption of conditional independence of the classifiers.

5.2.8 Decoding

In the decoding algorithm, classifications of multiple probes are combined to determine the prime word the subject is trying to communicate. If the codebook **C** is a matrix of n primes by m probes, indicating for each prime-probe-combination whether they are related or not. At the end of the sequence the prime word with the highest probability is selected by

$$\hat{i} = \underset{i}{\operatorname{argmax}} \left[P\left(c_{ij} | \mathbf{x}\right) \right] \tag{5.1}$$

where **x** is a vector of decision values, one for each probe. The probability for each target is calculated by combining the codebook and the individual decision values for each presented probe word:

$$P\left(c_{ij} | \mathbf{x}\right) = \frac{1}{Z} \cdot \prod_{j=1}^{m} P\left(c_{ij} | x_j\right) \tag{5.2}$$

where Z is an irrelevant normalisation constant, and where the probability a probe belongs to the class indicated in the codebook, given the decision value of the classifier is given by the logistic function,

$$P\left(c_{ij} | x_j\right) = \begin{cases} \frac{1}{1-e^{x_j}} & \text{if } c_{ij} = 1 \\ 1 - \frac{1}{1-e^{x_j}} & \text{if } c_{ij} = -1 \end{cases} \tag{5.3}$$

where related is assigned as the positive class, indicated by 1, and unrelated is assigned as the negative class, indicated by -1.

The probe to be presented next in the experiment is the probe for which the probability that the subject recognises it as related is closest to .5:

$$\hat{j} = \underset{j}{\operatorname{argmin}} \left(\left| \mathbf{v} \cdot \mathbf{C}' - 0.5 \cdot \mathbf{1}_m \right| \right) \tag{5.4}$$

where the codebook **C** again indicates which prime-probe-combinations are related and where **v** is the vector with the probabilities for each prime word based on the probes that have been presented so far:

$$v_i = P\left(c_i | \mathbf{x}\right) \tag{5.5}$$

Choosing the probability for a probe close to .5 optimizes the amount of information transmitted by the response:

$$I(p) = -p \cdot log_2(p) - (1-p) \cdot log_2(1-p) \tag{5.6}$$

5.2.9 Post-hoc analysis

A number of post-hoc analysis were performed to compliment the data obtained during the experiment. First an early stopping method was applied to determine at which point time the prime word sequence could be stopped without losing accuracy. A number of methods are discussed in Schreuder et al. (2013). Three of these methods (fixed number, Jin et al. (2011), and Höhne et al. (2010)) and an additional method not mentioned by Schreuder et al. (2013) were compared with not stopping. The additional method, thresholding the probability of a target given the data, as given in Equation (5.2), at 0.95, performed best and was selected for determining the stopping point. The last method The early stopping was first applied to the data gathered from the experiment, and later to all subsequent post-hoc analyses.

To obtain data that are too time-consuming to gather from subjects, post-hoc simulations were performed. The algorithm detailed in the decoding section above was implemented, where the classifier decisions were drawn from the decision values that were gathered during the experiment. Simulation results are obtained by simulating each word 100 times (iterations) for each subject and averaging over iterations, items and subjects, i.e., each number is the mean of 12.000 simulated prime sequences. The decision values were pooled per subject per block into a related and unrelated pool, based on the codebook constructed from the association database, i.e., not using the button presses.

The results from the experiments were simulated, by using the same parameters, to compare the simulation results to the data obtained in the experiment. However, where the experiment yielded one value per subject, per word, the simulations yielded 100.

To determine whether the information-based probe selection performs better than random probe selection, a simulation was run where the probes were selected at random.

To investigate whether the algorithm scales to larger numbers of prime words, the simulation was run with 150, 500, 1.000, 2.500, and 10.000 prime words.[1] In the experiment, 150 words were used as both prime words and probe words, resulting in a codebook (**C**) of 150x150. As a baseline for the scale to larger number of prime words a simulation was run where the maximum number of probe words were used (10.000), i.e., in the comparison only the number of prime words changes. The 150 prime words used in the experiment were always included and a random set of probe words was selected to supplement the total number of prime words to the required amount.

To evaluate the results of the post-hoc analyses, a number of measures were used: rank, proportion correct, number of probes, and Information Transfer Rate (ITR). The

[1]For the 10.000 prime words condition in fact only 9.270 prime words were used because that is the size of the Leuven dataset. For communication convenience we use 10.000 or 10k.

rank is defined as the position in the list of targets when sorted on their probability (see Equation (5.2)). The proportion correct can be indicated in three ways. The actual proportion correct ($\frac{correct}{total}$), the proportion related correct, where words that are related to the prime word are also counted in the numerator, and proportion in rank top 10, where words that have rank 1–10 are also counted in the numerator. The number of probes is simply the amount of probes that are used before reaching the stopping criterium. The Information Transfer Rate (ITR) is a measure that is often used to compare algorithms, because it incorporates accuracy, number of classes, and the time per classification. Wolpaw et al. (1998) defined the ITR for a Brain Computer Interface as:

$$B = V \cdot R \tag{5.7}$$

Where B is the ITR in bits per second, V is the amount of classifications per second, and R is defined as:

$$\begin{aligned} R = log_2(N) + P \cdot log_2(P) \\ +(1-P) \cdot log_2\left(\frac{1-P}{N-1}\right) \end{aligned} \tag{5.8}$$

ITR is often reported in bits per minute by multiplying B with 60.

5.3 Results

5.3.1 Grand average results

The grand average ERP results can be seen in Figure 5.4. The figure shows the ERPs for the related condition (in solid red) and unrelated condition (in dashed black) for channel CPz for each of the training block. The grey area indicates where the two conditions differ significantly, as indicated by the cluster-based non-parametric statistic described by Maris and Oostenveld (2007). The vertical dashed line indicates the grand-average reaction time, i.e., when subjects pressed the button. Channel CPz was chosen as a representative channel. The topo-plots of the time window indicated by the grey area in the ERP plot show the distribution of the effect over the scalp. Channels indicated with an asterisk are significant in this time window.

The grand average Time Frequency Representation (TFR) results are shown in Figure 5.5. Channel C3 was selected as a representative channel because right-hand motion is most strongly visible above the motor-cortex in the contra-lateral hemisphere. The data in Figure 5.5 are a normalised difference between the two conditions, obtained by first subtracting the TFR data from the unrelated condition from the related condition and then dividing the result by the sum of the two conditions ($\frac{related-unrelated}{related+unrelated}$). The area

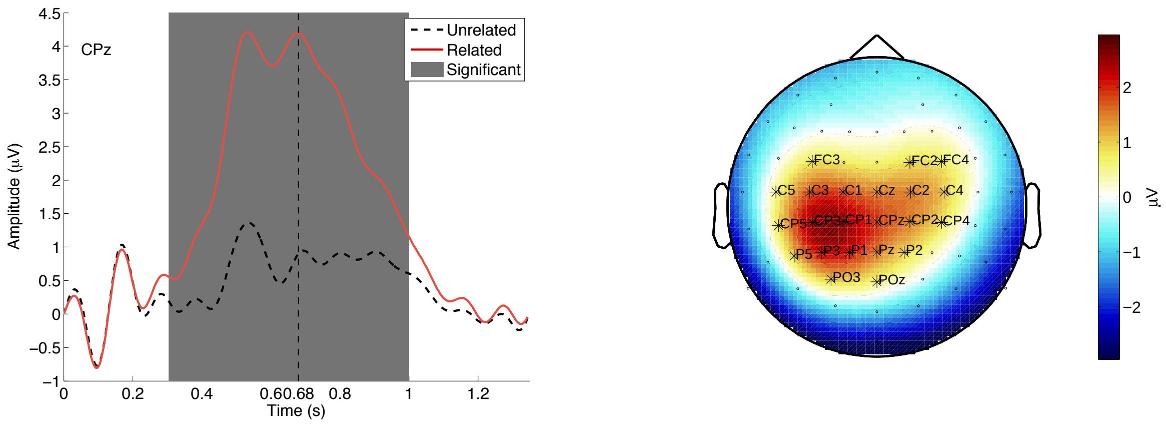


Figure 5.4: **Grand Average ERP:** Grand average Event Related Potential (ERP) results for the training block. Left: the ERPs for the related (solid red) and unrelated (dashed black) conditions. The grey area indicates where the conditions differ significantly. The dashed vertical line indicates the average reaction time, i.e., when the subjects pressed the button. Right: The distribution over the scalp of the significant difference (related – unrelated) averaged over the grey area of the left panel (260ms – 1000 ms). Asterisks indicate for which channels the effect is significant.

within the grey box is where the two conditions are significantly different, as indicated by the cluster-based non-parametric statistic described by Maris and Oostenveld (2007).

5.3.2 Classification results

An overview of the single trial classification results is shown in Table 5.1. All reported accuracies are significantly different from chance level (0.5), with p-value of < .001, based on a binomial test (Allison et al. 2013, Ch. 17).These classification results are based on the labels that are taken from the Leuven dataset.

To investigate how well the Leuven dataset represents the associations by the subjects and whether that is influenced by the difference in association strength per block (shown in Figure 5.3), the mismatch between the labels as given by the Leuven dataset (used during the experiment) and the labels that were derived from the button presses of the subjects during the experiment was calculated. The average proportion of mismatched labels per block can be seen in Figure 5.6. Because in the test blocks, some prime-probe combinations may occur multiple times, only the mismatch for unique combinations it calculated.

An overview of the decoding results can be found in Table 5.2. It shows the proportion correct in the situation where all 100 probes are used (Full) and in the situation

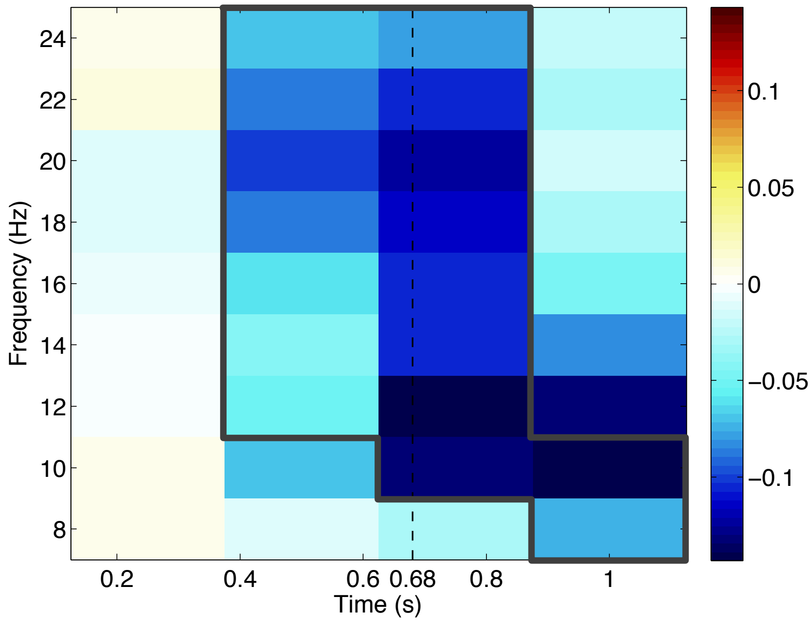


Figure 5.5: **Grand Average TFR:** Grand average TFR results for the training block for channel C3. The data shown here is a normalised difference between the related and unrelated conditions, obtained by $\frac{related-unrelated}{related+unrelated}$. The grey box indicates in which parts of the figure the difference between the two conditions is significant. The vertical dashed line indicates the grand average reaction time, i.e., when the subjects pressed the button.

where early stopping is applied (Stop). Asterisks indicate whether the accuracy is significantly different from chance level (1/150, 0.00667), based on a binomial test.

5.3.3 Post-hoc simulation results

The results for the post-hoc simulations can be found in Figure 5.7. It shows the performance on the four measures mentioned earlier: proportion correct (top-left panel), rank (top-right panel), number of probes (bottom-left panel), and Information Transfer Rate (ITR) (bottom-right panel). The different simulations are arranged on the x-axis. From left to right: (i) the results from the experiment using the full number of probes (Exp Full), (ii) the results from the experiment with early stopping (Exp), (iii) simulation results with early stopping (Sim), (iv) simulation with random probe selection and early stopping (Rand Sim), (v) simulation with 150 targets and 10.000 probes with early stopping (Sim 150 x 10k), (vi) simulation with 10.000 targets and 10.000 probes with early stopping (Sim 10k x 10k).

To determine whether the simulation results differ significantly, four Bonferroni cor-

	Train	Test 1	Test 2	Post-train
S1	85%	75%	73%	80%
S3	75%	66%	65%	80%
S4	87%	74%	77%	87%
S5	74%	65%	65%	76%
S6	79%	62%	64%	70%
S7	75%	60%	59%	67%
S8	74%	61%	64%	70%
S9	73%	65%	63%	66%
S10	73%	66%	69%	83%
S11	88%	62%	66%	83%
Mean	78%	66%	67%	76%
IM	76%	66%	67%	72%

Table 5.1: **Classification accuracies:** Single trial classification accuracies, based on relatedness labels from the Leuven dataset. All classification accuracies differ significantly from chance level (0.5) with a p-value of $< .001$.

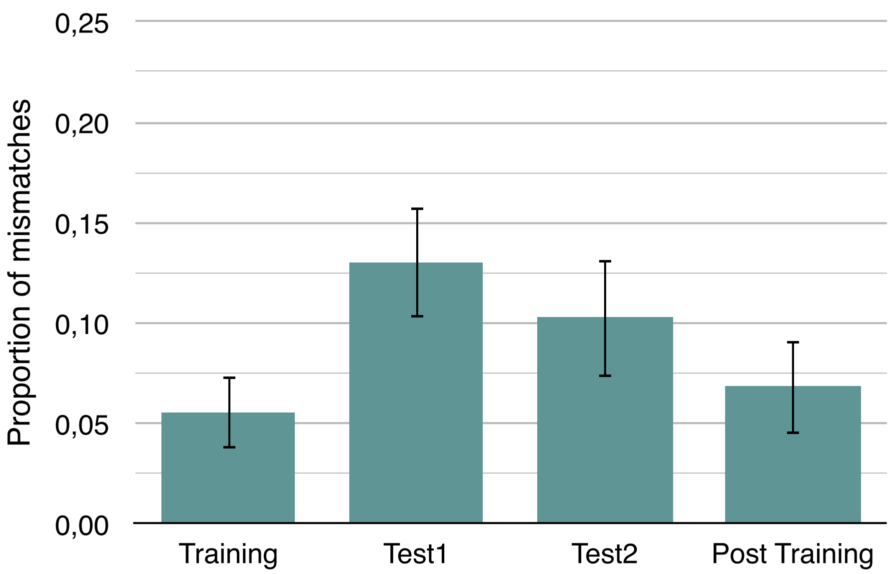


Figure 5.6: **Mismatch:**Mismatch between codebook based on Leuven association dataset and button presses. Only the unique mismatches were counted. Error bars are corrected for a within subject design (Field et al. 2012, p. 361–366).

rected one-way repeated measures ANOVA's were performed, with factor condition with the six analyses as levels. When the ANOVA was significant, bonferroni corrected

	Full	Stop	Probes
S1	83% **	42% **	29
S3	50% **	58% **	36
S4	50% **	42% **	28
S5	25% *	33% **	58
S6	8%	25% *	54
S7	8%	17%	52
S8	42% **	58% **	66
S9	33% **	33% **	75
S10	42% **	50% **	43
S11	42% **	50% **	33
Mean	38% **	41% **	47
IM	58% **	33% **	34

Table 5.2: **Decoding results:** First two columns indicate proportion correct, last column indicates the number of probes used to obtain the accuracy for the *stop* condition, for the *full condition* this is always 100. Asterisks indicate whether the proportion correct differs significantly from chance level (1/150, 0.00667). * indicates .001 $< p <$ .05, ** indicates $p < .001$.

post-hoc contrasts were performed using Student's dependent samples t-test. The contrasts of interest were: Exp Full vs Exp, Exp vs Sim, Sim vs Rand Sim, and Sim 150 x 10k vs Sim 10k x 10k. Only the significant contrasts are reported below.

There was a significant difference in proportion correct between the six analyses, $F(5,45) = 13.8$, $p < .001$, $\eta_p^2 = 0.353$. The post-hoc contrasts showed that the proportion correct with intelligent probe selection (M = 0.307, SD = 0.14) is significantly higher than the proportion correct with random probe selection (M = 0.122, SD = 0.0875), $p(9) = 6.79$, $p < .001$. It also showed that the proportion correct in the simulation with 150 targets and 10.000 probes (M = 0.344, SD = 0.142) is significantly higher than the proportion correct in the simulation with 10.000 targets and 10.000 probes (M = 0.191, SD = 0.108), $t(9) = 6.61$, $p < .001$.

There was a significant effect on rank for the six analyses, $F(5,45) = 24$, $p < .001$, $\eta_p^2 = 0.568$. Post-hoc contrasts showed that the rank in the simulation with 150 targets and 10.000 probes (M = 18.6, SD = 18.4) is significantly higher than the rank in the simulation with 10.000 targets and 10.000 probes (M = 73.4, SD = 24.7), $t(9) = -9$, $p < .001$.

There was also a significant difference in the number of probes used in the different analyses, $F(5,45) = 52.9$, $p < .001$, $\eta_p^2 = 0.635$. The post-hoc contrasts showed that the number of probes used in the experiment without early stopping (M = 100, SD = 0)

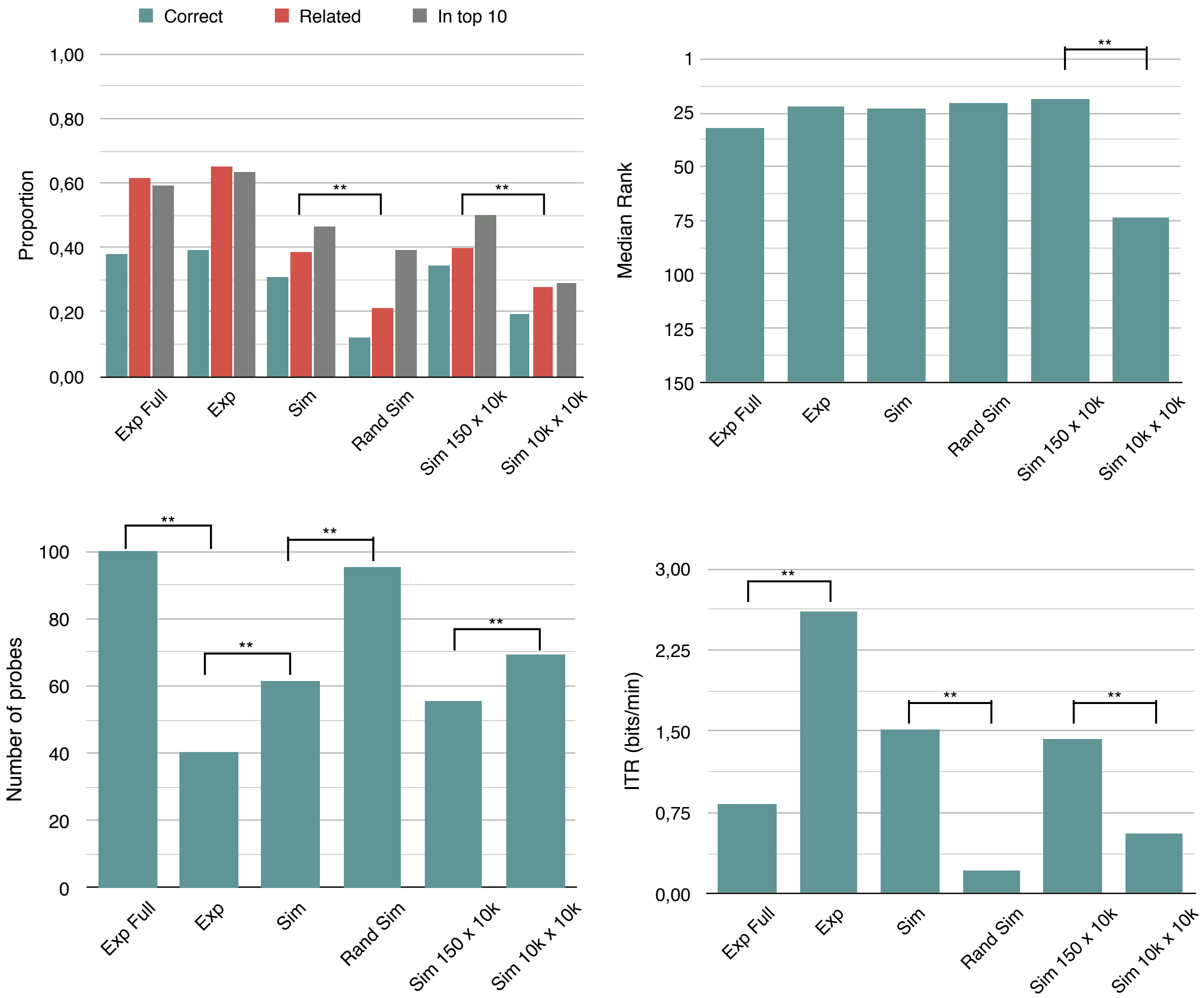


Figure 5.7: **Post-hoc simulations:** Results for post-hoc simulations: Exp Full: the experiment using the full number of probes, Exp: results from the experiment with early stopping, Sim: simulation results with early stopping, Rand Sim: simulation with random probe selection and early stopping, Sim 150 x 10k: simulation with 150 targets and 10.000 probes with early stopping, Sim 10k x 10k: simulation with 10.000 targets and 10.000 probes with early stopping. Top-left: Proportion correct, related correct and in top 10. Top-right: Rank, the rank for the last analysis (Sim 10k x 10k) is scaled by dividing by 61.8. Bottom-left: Number of probes. Bottom-right: Information Transfer Rate. * indicates $.001 < p < .05$, ** indicates $p < .001$.

is significantly higher than when applying the early stopping algorithm (M = 40.7, SD = 20.1), $t(9) = 9.31$, $p < .001$. It also showed that the number of probes used in the experiment with early stopping (M = 40.7, SD = 20.1) is significantly lower than the number used in the simulation with early stopping (M = 61.6, SD = 20.8), $t(9) = -7.45$, p

$<$ .001. Furthermore, the number of probes used with intelligent probe selection (M = 61.6, SD = 20.8) is significantly lower than the the number of probes used with random probe selection (M = 95.1, SD = 6.78), *p*(9) = -6.72, p $<$ .001. Finally, the number of probes used in the simulation with 150 targets and 10.000 probes (M = 55.6, SD = 19) is significantly lower than the number of probes used in the simulation with 10.000 targets and 10.000 probes (M = 69.1, SD = 21.4), *t*(9) = -9.77, p $<$ .001.

A significant difference in Information Transfer Rate (ITR, see Equation (5.5)) was also found, F(5,45) = 15.2, p $<$ .001, η_p^2 = 0.349. Post-hoc contrasts showed that the ITR in the experiment without early stopping (M = 0.835, SD = 0.633) is significantly lower than when applying the early stopping algorithm (M = 2.6, SD = 1.59), *t*(9) = -4.91, p = 0.003. Furthermore, the ITR with intelligent probe selection (M = 1.52, SD = 1.52) is significantly higher than the the ITR with random probe selection (M = 0.222, SD = 0.255), *p*(9) = 3.21, p = 0.042. It also showed that the ITR in the simulation with 150 targets and 10.000 probes (M = 1.53, SD = 1.2) is significantly higher than the ITR in the simulation with 10.000 targets and 10.000 probes (M = 0.668, SD = 0.758), *t*(9) = -9.77, p $<$ .001.

For the scaling to larger vocabularies (more prime words), further simulations were performed, where the number of prime words were gradually increased from 150 to 10.000. The results and a fit of this data can be seen in Figure 5.8. It shows that the proportion correct decreases logarithmically with vocabulary size with formula $0.59 - 0.099 \cdot log(x)$, where x is the vocabulary size in number of possible prime words. The rank decreases according to a power law function: $0.088 + x^{-0.1}$. The number of probes until the stopping criterium is reached increases logarithmically approximately according to $40 + 7.3 \cdot log(x)$. The ITR can roughly be fit with a polynomial after a log(x) transformation: $-0.074x^2 + x - 1.9$, peaking at a vocabulary size of 1214.

5.4 Discussion

The grand average Event Related Potential (ERP) results show a significant P300 effect. The timing of the peak and distribution over the scalp are similar to paradigms eliciting a P300 response (Polich 2007). The peak of the response, on average, occurs shortly before the button press, indicating the brain response comes before the button press. The grand average Time Frequency Representation (TFR) results show a significant negative difference in the mu-band, corresponding to the brain activity normally elicited by a finger movement (Pfurtscheller and Lopes da Silva 1999). When looking at the evolution of the difference topography of the ERS in the 10–14 Hz frequency band, it also shows an expected pattern: no difference in the first window (0–250ms), and then an increasing (negative) difference over motor cortex, see Figure 5.9 in the additional figures

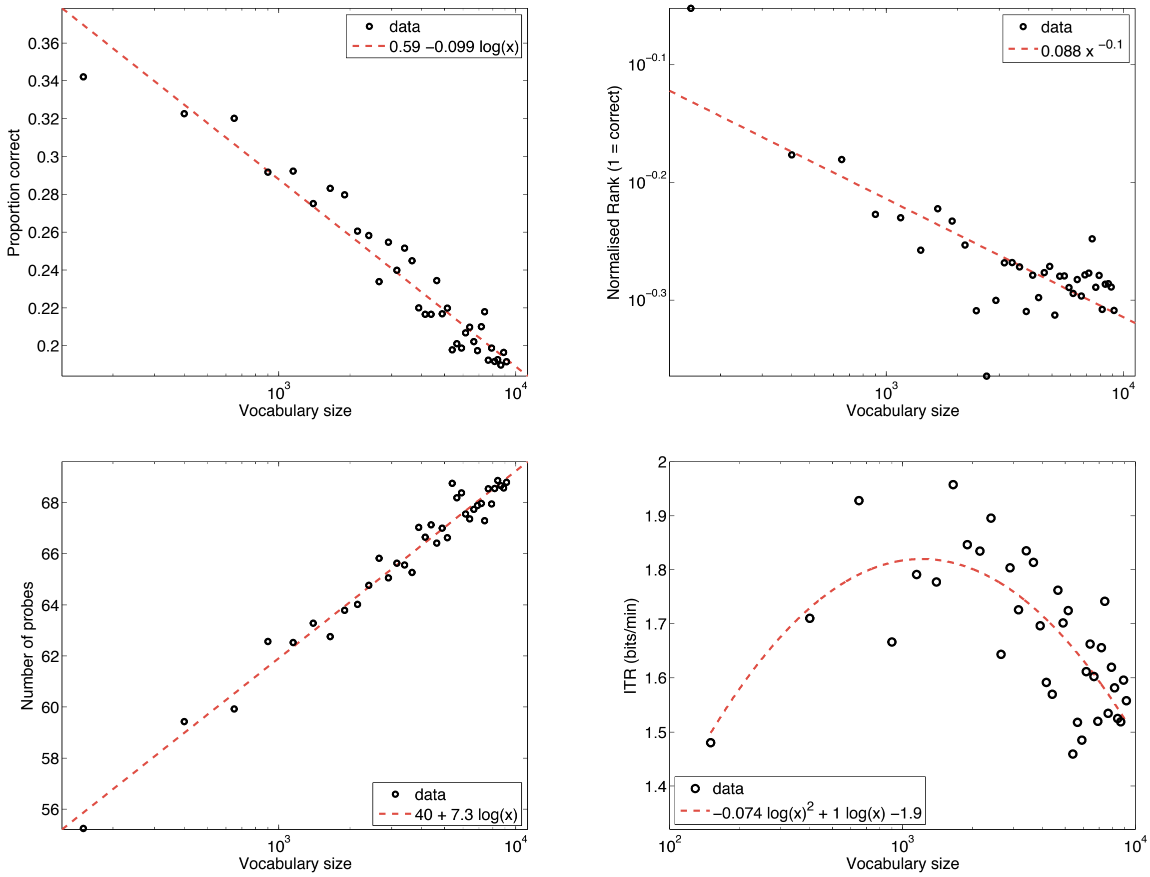


Figure 5.8: **Performance scaling:** Scaling of the performance of the BCI with larger vocabularies. The vocabulary size is plotted on the x-axis. The simulation results are indicated by the black circles. A fit of the data is displayed with a dashed red line. Top-left: results for proportion correct, the data were fitted with a logarithmic function. Top-right-panel: simulation rank, the data were fitted with a power law function. Bottom-left: number of probes, data were fitted with a logarithmic function. Bottom-right: Information Transfer Rate (ITR), the data were fitted with a second order polynomial after a log transformation, peaking at a vocabulary size of 1214.

section at the end of this chapter. The single trial accuracy on the test items is on average 67%. However, there is a difference of about 10% between the training / post-training and the test items.

The mean decoding accuracy is 38% using the full 100 probes, and 41% when applying early stopping. The Information Transfer Rate (ITR) is 0.835 bits/min with the full 100 probes and 2.6 bits/min with early stopping. The post-hoc simulations show that the performance of the algorithm is significantly better with the intelligent probe selection algorithm than with random probe selection. The simulations also show that the performance scales logarithmically with vocabulary size (number of possible prime words).

A consistent difference in single trial accuracy between training block and test blocks was found. On average, the accuracy of the test blocks was 10% lower than that in the training block. There is often a lower accuracy in test blocks than in the training blocks caused by non-stationarities in the data. The more time between the training block and the test block, the lower the test accuracy. However, this does not seem to be the case here. The accuracy on the post-training block, which occurs furthest away in time from the training block, has a similar accuracy to the training block. There are some differences in the stimuli that might explain the lower accuracy. The mean association strength in the test-items is lower than the strength of the training-items (see Figure 5.3). Another hypothesis could be that there is a higher mismatch between codebook and button press found in the test sets. This in turn would decrease the single trial accuracy because the labels do not match with when the subject actually moves. However, this does not seem to be the case as the single trial accuracy where the button presses are used as labels, the 10% drop in accuracy remains. Future research efforts should give more insight into the cause of this performance mismatch.

As mentioned before, there is a mismatch between the associations as indicated by the Leuven dataset and the subjective associations of the subjects as indicated by their button presses. This mismatch is shown in Figure 5.6. The inverse of the mismatch could be seen as a measure of fit of the Leuven dataset. In that case, the overall fit of the dataset is 91%. There is a difference in fit between the training blocks (94% fit) and test blocks (88% fit). This difference could be explained by the difference in association strength between the blocks (see Figure 5.3). The test blocks have a lower association strength compared to the training blocks. It could be expected that with lower association strengths less people would agree that items are indeed related, decreasing the fit on those particular items.

An early stopping algorithm was applied to the data obtained in the experiment. When the probability of any prime word in the decoding algorithm reached the threshold of .95, the decoding was stopped with that prime word as output. On average the proportion correct did not change, however a significant lower number of probes is used to reach this same accuracy. In other words, it takes less time without affecting the performance, which in turn increases the Information Transfer Rate (ITR) of the BCI.

It was shown here that the intelligent probing algorithm contributes significantly to the performance of the BCI. It increases the accuracy, decreases the number of probes required, and increases the ITR of the BCI. It is also expected, that this difference will become even more pronounced with a larger vocabulary (now 150 words).

Offline simulations found that increasing the vocabulary size resulted in a drop in performance, however this was not proportional to the increase. The proportion correct and number of probes change logarithmically with the vocabulary size. The rank decreases according to the power law and the ITR can be fitted with a polynomial after a log transformation. The maximum of this polynomial occurs at a vocabulary size of about 1.200. This means that the BCI conveys the most information with that vocabulary size.

It has been shown here that the BCI works by measuring subject's actual movement. According to Blokland et al. (2013) actual movement is closer in brain signature to attempted movement, i.e., when paralysed subjects try to make an actual movement, than imagined movement. The subject with the best performance returned to do the experiment again with imagined movement. A comparison between this subject's data in the actual movement session and in the imagined movement sessions was made. It showed that the ERP results were almost identical between the two conditions. In the TFR, the imagined movement had a similar pattern, but a lower amplitude, which is in line with the previous research (McFarland et al. 2000). See Figure 5.10 and Figure 5.11 in the additional figures section at the end of this chapter. The classification results are also almost identical to the grand average movement results and show that this BCI could also work based on imagined movement.

The codebook used by the BCI, based on the Leuven association dataset (De Deyne and Storms 2008) is sparse and not optimal. Results show a difference between the associations based on the dataset and the associations as judged by the subjects, i.e., the mismatch mentioned earlier. The single trial classification results could be improved by using the labels given by the subjects during the experiment. However, it is not possible to improve the decoding process by using these labels. In order for the decoding to be fair, all possible combinations of prime and probe words need to be manually labelled by the each subject. With a vocabulary size of 150 words, there are already 11.175 combinations, which would take about 4,5 hours to label. Increasing the vocabulary size to the earlier mentioned optimum 1.200 words, increases the combinations to 719.400 (about 280 hours). So for smaller codebooks, some time could be spent in optimising the codebook to further increase the performance of the BCI.

A way to keep the vocabulary size small is to use context to construct the vocabulary. When the BCI is to be used by a patient who wants to communicate about wishes (e.g., *I would like some coffee*) and feelings (e.g., *my leg hurts*), words needed to communicate this could be selected as the vocabulary. By using this context, the total number of words could be kept relatively small, allowing for a similar performance as reported here, and allowing the patient to manually label all possible combinations for improved performance.

The proposed BCI could be useful for two different groups of patients. First, the group of locked-in patients who are not able to communicate anymore. For these patients, this BCI could be an alternative for the existing (visual) spellers. Instead of spelling a word letter by letter, the word or concept is communicated directly using the semantic relations BCI. Further research is needed to determine which method patients prefer. The BCI would also work when pictures or auditory presented words are used instead of visually presented words. This would open up the application for patients that are not able to read, due to illiteracy or other causes. Second, the group of patients with aphasia, especially the patients where the recognition is still intact, but language production is impaired and spelling itself is impossible or very slow. These patients would not need the brain control. For these patients the button-presses themselves can be used, dramatically increasing the performance of the system. Simulations with perfect classification accuracy show perfect decoding accuracy after about 18 probes, and an ITR of around 23 bits per minute.

A different way to detect concepts or words could result from the work of Huth et al. (2012), Simanova et al. (2012), or Schoenmakers et al. (2013). They attempt to decode concepts, words, or images from the brain by looking at activation patterns measured by functional Magnetic Resonance Imaging (fMRI). Currently this still requires presenting stimuli to the subjects and decoding the response to these stimuli. However in future it may be possible to decode this information when the subject has the stimulus in mind.

5.5 Conclusions

This chapter shows that (i) it is possible to build a BCI based on semantic relations using an intelligent probing algorithm, (ii) Applying a dynamic stopping technique significantly contributes to the performance of such a BCI, (iii), the intelligent selection algorithm contributes significantly to the performance of the BCI, and (iv) the number of required probes increases slowly (logarithmically) with increasing numbers of probe words and primes.

Acknowledgments

We gratefully acknowledge the reviewers for their comments that helped to improve the manuscript.

5.6 Additional Figures

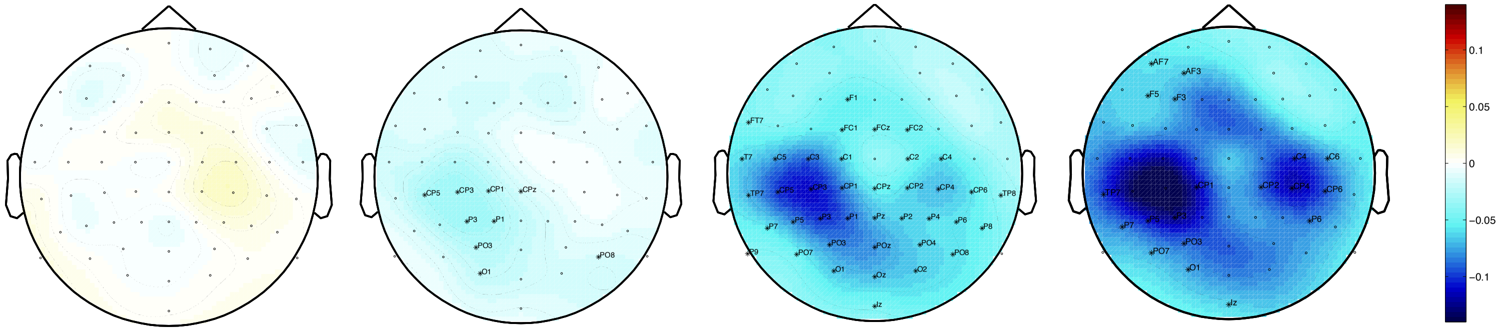


Figure 5.9: **Evolution of band power topography:** Difference topography (related/movement - unrelated/no movement) in the 10–14 Hz frequency band. The respective time windows of the topographies are: 0–250ms, 250–500ms, 500–750ms and 750–1000ms. Asterisks indicate channels with significant differences in all frequency bins between 10 and 14 Hz.

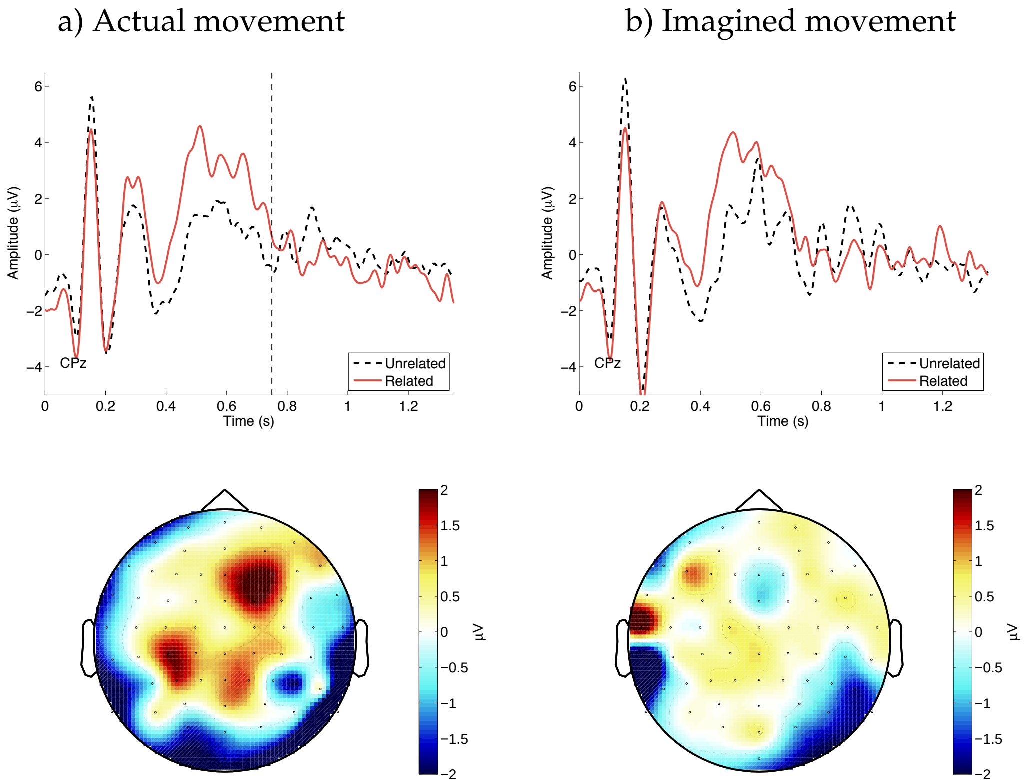
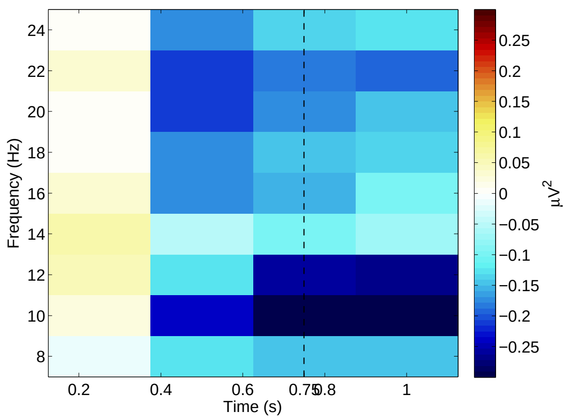


Figure 5.10: Single subject ERP, actual movement (a) vs imagined movement (b): Single subject Event Related Potential (ERP) results for the training block. Top: the ERPs for the related (solid red) and unrelated (dashed black) conditions. The dashed vertical line indicates the average reaction time, i.e., when the subjects pressed the button. Bottom: The distribution over the scalp of the significant difference (related – unrelated) averaged over the significant area from the grand average analysis: 260ms – 1000 ms. The topographies show similar structure in both conditions, with a large central positivity (red/white color), surrounded by a peripheral (primarily occipital) negativity.



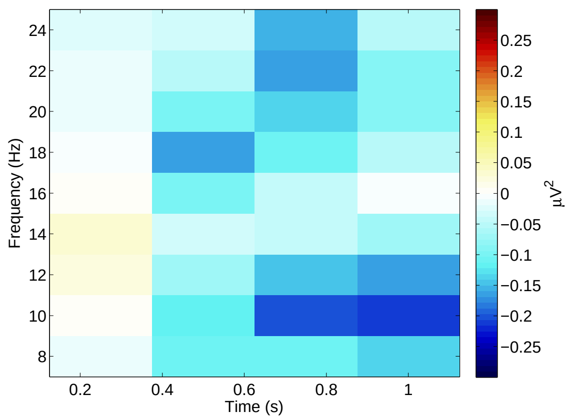


Figure 5.11: **Single subject TFR, actual movement vs imagined movement:** Single subject TFR results for the training block for channel C3. The data shown here is a normalised difference between the related and unrelated conditions, obtained by $\frac{related-unrelated}{related+unrelated}$. The vertical dashed line indicates the grand average reaction time, i.e., when the subjects pressed the button. Left: The actual movement session. Right: the imagined movement session.

Chapter 6

General Discussion

6.1 Summary

Brain Computer Interfaces (BCI) translate measured brain activity into output commands. These output commands can be used to control, for example, a computer, a wheelchair, or they can be used to communicate. The last is the focus of this thesis. Many communication BCIs have been developed since the first visual speller by Farwell and Donchin (1988). Although the performance of these communication BCIs has increased over the years, there are still many possible improvements. The four research chapters describe improvements to communication BCIs and are summarized below.

Chapter 2 investigated the effect of varying different stimulus properties on performance of the visual speller. Each of the different stimulus properties have been tested in previous literature and have a known effect on visual speller performance. This chapter investigated whether a combination of these types of stimuli can lead to a greater improvement. It was found that higher stimulus rates can improve the visual speller performance and can lead to less time required to train the system. It was also found that a proper stimulus code can overcome the stronger response to rows and columns, but can not greatly improve speller performance.

In chapter 3, a tactile speller was developed and compared with existing visual speller paradigms in terms of classification performance and elicited ERPs. The fingertips of healthy participants were stimulated with short mechanical taps while EEG activity was measured. The letters of the alphabet were allocated to different fingers and subjects could select one of the fingers by silently counting the number of taps on that finger. The offline and online performance of the tactile speller was compared to the overt and covert attention visual matrix speller and the covert attention Hex-o-Spell speller. For the tactile speller, binary target versus non-target classification accuracy was 67% on average. Classification and decoding accuracies of the tactile speller were lower than for the overt matrix speller, but higher than for the covert matrix speller, and similar to Hex-o-Spell. The average maximum information transfer rate of the tactile speller was 7.8 bits/minute (1.51 char/min), with the best subject reaching a bit-rate of 27 bits/minute (5.22 char/min). An increased amplitude of the P300 ERP component was found in response to attended stimuli versus unattended stimuli in all speller types. In addition, the tactile and overt matrix speller also used the N2 component for discriminating between targets and non-targets. Overall, this chapter shows that it is possible to use a tactile speller for communication. The tactile speller provides a useful alternative to the visual speller, especially for people whose eye gaze is impaired.

Chapter 4 aims at detecting semantic priming at the single-trial level. By using machine learning techniques it is possible to analyse and classify short traces of brain activity, which could, for example, be used to build a Brain Computer Interface (BCI). The chapter describes an experiment where subjects were presented with word pairs and asked to decide whether the words were related or not. A classifier was trained to determine whether the subjects judged words as related or unrelated based on one second of EEG data. The results show that the classifier accuracy when training per subject varies between 54% and 67%, and is significantly above chance level for all subjects (N = 12) and the accuracy when training over subjects varies between 51% and 63%, and is significantly above chance level for 11 subjects, pointing to a general effect.

Chapter 5 investigates a possible Brain Computer Interface (BCI) based on semantic relations. The BCI determines which prime word a subject has in mind by presenting probe words using an intelligent algorithm. Subjects indicate when a presented probe word is related to the prime word by a single finger tap. The detection of the neural signal associated with this movement is used by the BCI to decode the prime word. The movement detector combined both the evoked (ERP) and induced (ERD) responses elicited with the movement. Single trial movement detection had an average accuracy of 67%. The decoding of the prime word had an average accuracy of 38% when using 100 probes and 150 possible targets, and 41% after applying a dynamic stopping criterium, reducing the average number of probes presented to 47. The chapter shows that the intelligent algorithm used to present the probe words has a significantly higher performance than a random selection of probes. Simulations demonstrate that the BCI also works with larger vocabulary sizes, and the performance scales logarithmically with vocabulary size.

6.2 Research Questions

First, improvements were made to the existing visual speller as developed by Farwell and Donchin (1988), where the following research questions were answered: (i) *Does visual speller performance suffer from high stimulus rates?* Yes, the single event accuracy of the visual speller suffers from higher stimulus rates, but the letter accuracy does not. (ii) *Does an increase in stimulus rate lead to a lower training time for an online visual speller?* Yes, the increase in stimulus rate indeed allows for less time required to train a classifier. There also exists a trade-off between training time and integration time that holds at all stimulus rates. (iii) *What aspect of the difference in the event related potential to a flash or a flip stimulus causes the increase in accuracy?* There are significant differences in the ERPs of the flash and the flip stimulus that affect the classification. There is more class relevant information in the early response for the flip stimuli than for the flash stimuli. In the late response this is reversed, making the flip stimulus more robust at higher stimulus rates. (iv) *Can an error-correcting (dense) stimulus code overcome the reduction in performance associated with decreasing target-to-target intervals?* Yes, a well designed stimulus code is able to overcome adverse effects of decreased target-to-target intervals, but is not able to greatly increase the speller performance.

Next was a move away from visual, gaze dependent, spellers to a tactile speller, answering the following questions: (i) *What is the performance of a tactile speller?* The accuracy of the visual speller varied per subject between 54% and 67% when the classifier was trained on each subject individually. (ii) *How does the tactile speller compare to the overt and covert visual speller and the covert Hex-o-Spell?* The tactile speller had a lower performance than the overt visual speller, but a higher performance than the overt visual speller. The performance of the tactile speller and the covert Hex-o-Spell were similar.

Then, research was directed toward communication per word instead of per letter, by looking at semantic priming and answering the following question: (i) *Is it possible to detect semantic priming at the single trial level?* Yes, the detection rate was significantly above chance-level for all subjects varying between 54% and 67%.

Last, the possibility of developing a BCI based on semantic relations was investigated by answering the following questions: (i) *Is it possible to build a BCI based on semantic relations using an intelligent probe selection algorithm?* Yes, it is possible. However, the implemented algorithm only works well when the underlying classification rate of the relatedness is 70% or higher. (ii) *Does applying a dynamic stopping technique contribute to the performance of this BCI?* Yes, applying an early stopping technique lowers the amount of time required to make a decoding decision without significantly affecting the accuracy, leading to a significant increase in performance (as measured by the information transfer rate). (iii) *Does intelligent selection contribute to the performance of the BCI?* Yes, intelligent selection leads to a better performance than random selection of probe words. This effect becomes even more pronounced when working with larger vocabularies. (iv) *Do the results of the BCI scale to large numbers of prime and probe words?* Yes, the number of required probes increases slowly (logarithmically) with increasing numbers of probe words and primes.

Above, the low-level research questions of the various chapters were answered. The overarching question of this thesis was: *How can communication using a brain computer interface be improved?* Multiple improvements to communication BCIs were proposed and investigated. Some directed towards increasing the performance of the BCI and others towards an increased usability by the target group. Currently, there seems to be a tradeoff between accuracy and speed on one hand and usability on the other hand. When an attempt is made to improve upon the usability (e.g., an eye-gaze independent BCI), this leads to a decrease in accuracy and/or speed. An explanation for this could be that the improvements on usability result in a (fundamentally) different BCI. For example the tactile speller and the semantic relations BCI differ in fundamental aspects from the original visual speller by Farwell and Donchin (1988). Research into these BCIs starts almost from scratch, where the original has been researched for more than 25 years.

In the next section some more improvements to the BCIs described in this thesis and to communication BCIs in general are discussed as points of future research.

6.3 Future directions

The research described in this thesis has all been conducted with healthy subject as a proof of principle. The ultimate goal of the BCIs described herein is to support patients in their daily functioning. To achieve this, the BCI needs to be thoroughly tested with patients, both in the lab and in their home environment. Some steps in this direction have already been taken. Severens (2013, chapter 4) have tested the tactile speller described in chapter 3 with ALS patients in a laboratory setting. They found that the BCI had similar performance with patients as with healthy subjects. The binary classification accuracy was around 60% (chance-level of 50%) and the 6-class decoding had an accuracy of 55% (chance-level of 17%). The BCI had a performance significantly above chance-level for all patients, though not for all healthy subjects.

Within the Braingain consortium, considerable effort has been made to move the speller BCI into the homes of patients. Collaboration has been set up with a Dutch supplier of home automation systems. This company, Quo Vadis (`www.qvn.nl`), supplies home automation systems, including The Grid 2 software package by Sensory Software (`www.sensorysoftware.com`). A BCI link has been made with this software and is currently being tested with patients. An advantage of working with this existing software is that patients are already familiar with the Grid software and control it with their residual movement abilities. Once they lose that they can switch to brain control and continue using the same software. The Grid software not only enables communication, but also allows the patient to operate their computer and control their home automation system.

Another future direction is the continuation of spelling with words or concepts. The word communication BCI described in this thesis is only a first implementation. Further improvements could be made in several areas. The mental task that drives the selection algorithm could be changed or improved upon. The semantic relations database that is currently used could be improved and updated. Also the selection and decoding algorithm itself could be further improved. As mentioned in chapter 5, this word communication speller could also be useful for aphasic patients. However, they would not be using a BCI. An iPhone and iPad app has been developed with the same algorithm as used in the semantic relations BCI. This app, called *WoordPrikker*, allows users to indicate wether a word is related, unrelated, or the word they are trying to communicate, and works in the same way as the BCI. However, thanks to the certainty of the responses the app has a very high performance.

In the introduction the chat-by-click technology, described by Geuze et al. (2008) was mentioned. The chat-by-click technology uses a conversation database that can be traversed by alternate selection of two parties. The use of the conversation database limits the scope of the conversation that the system supports, but also greatly increases the speed of conversation, as complete sentences can be communicated with one single click. An effort is currently being made to increase the number of conversation databases. Also an iPad app based on this principle is being developed, called *cChats*. Future research could be directed to the question how this technology can be incorporated into a communication BCI and to develop conversations tailored to the BCI user.

6.4 Conclusion

Brain Computer Interfaces for communication is a relatively new research field. Large steps have been made since its inception, but the current state of the art is not able to compete with existing control methods, e.g., mouse and keyboard. For some select groups of patients that are not able to use these methods, a BCI could be a solution. However, performance of BCIs in general is still far from optimal. It is clear that making a practical BCI for patients is a difficult problem which requires improvements on the existing systems in many areas. This thesis has shown some possible improvements, by using better stimulus encoding, using more appropriate stimulus modalities or trying to detect higher level cognitive concepts. Whilst all of these approaches show some promise, none was the 'silver bullet' which would make useable BCIs a reality. In fact whilst it is clear that patient BCIs will be useful in the next few years, it is also clear that much more work is needed before they represent a viable alternative communication modality for the majority of patients and can be moved out of the lab and into the homes of users in need.

Glossary

Attempted movement Similar to imagined movement, but here subjects are not able to actually move, for instance due to paralysis.

Chance-level Indicates the percentage correct, if the classifier would have random output. This is given by $\frac{1}{N} \cdot 100\%$, where N is the number of classes. In the case of a binary classifier, $N = 2$, so the chance-level is 50%.

Character A character displayed on the screen that a subject can attend to / select.

Classes Classes are the categories the classifier is able to distinguish. Many classifiers have two classes and are called binary classifiers. They group the data into two categories.

Code A way of representing stimulus events over time.

Codebook Describes how a complex intention is built up from single event classifications. For example in the case of the visual speller, the codebook indicates for each character at which time it is accentuated, thus at which times a P300 response should be detected for that character to be the intended character.

Common Average Reference (CAR) Technique where an average over all channels is subtracted from each channel. This removes noise from outside the head, as this noise is common over all channels.

Covert attention Subjects pay attention to on item on the screen, but are not directing their gaze to that object. Often they look at a fixation at the center of the screen.

Decoding Combining multiple single event classifications to decode a complex intention of the subject. By combining the single event classifications with a codebook a more complex intention can be communicated.

Electroencephalogram (EEG) Technique for measuring the electrical activity of the brain by placing sensitive electrodes on the scalp and measuring the differences in potential over the scalp.

Electromyogram (EMG) Technique for measuring muscle tension, by placing an electrode on the muscle and measuring the electrical potential resulting from tensing the muscle.

Epoch An epoch is the piece of data that needs to be categorized.

Event related desynchronization (ERD) Activation pattern in the time frequency representation (TFR), where neurons start firing out of sync, leading to a decrease in measured EEG or MEG power or amplitude.

Event related potential (ERP) Brain response time-locked to the onset of an event or stimulus. Often used for an average over many examples, but in BCI context also used for single trials in the time-domain.

Event related synchronization (ERS) Activation pattern in the time frequency representation (TFR), where neurons start firing in sync, leading to an increase in measured EEG or MEG power or amplitude.

Example The epochs for which the label is already known and are used to train the classifier..

Feature Epochs consist of features, individual data points, e.g., time-points for a number of EEG-channels, that are used by the classifier to categorize the epoch.

Flash Accentuation by change of luminance.

Flip Accentuation by rotating a rectangle on which a character is superimposed.

Grand average (GA) Indicates that the resulting data is averaged over all trials and all subjects.

Imagined movement Mental task often used in BCI, a certain movement is imagined by the subject, but not actually performed. Subjects are often asked to imagine what it would feel like if they were to make the movement.

Information Transfer Rate (ITR) A measure to compare brain-computer interfaces, which includes the number of classes, the classification accuracy and the time per classification.

Integration time The time over which binary decisions are collected before making a multi-class decision.

Label A label is attached to an epoch to indicate to which class it belongs. Epochs in the training set have known labels, while in the test set the labels need to be provided by the classifier.

Letter accuracy Accuracy with which the decoder is able to determine which character is being attended based on a number of stimulus event classification decisions.

N2 The N2 is a negative going wave peaking around 200 ms after stimulus onset. The visual N2 is measured in the occipital channels over the visual cortex and is linked to movement detection.

N400 Negative going ERP peaking around 400 ms that is modulated by semantic priming. Unrelated probes elicit a more negative N400 than related probes.

Overt attention Subjects pay attention to and direct their gaze to an item on the screen.

P300 Positive going brain response peaking at around 300 ms after stimulus onset. Often elicited by the oddball paradigm, where multiple stimuli are presented and one of stimuli has a certain importance. When the important stimulus is presented the P300 occurs.

Prime word Word that is used to prime the subject.

Probe word Word that is used to elicit a priming response. When a word a probe word is related to a prime word, the N400 response is smaller than when it is unrelated.

Pseudo-random noise (PRN) Stimulus pattern where each character is highlighted according to its own pseudo-random noise code.

Regularization A penalty on complex solutions of the classifier to prevent over-fitting and increase the generalizability of the classifier.

Row-column (RC) Stimulus pattern where stimuli are highlighted in rows and columns.

Sequence Period during which a (complex) intention is decoded, often linked to a sequence of stimuli. In the case of the standard visual speller, there is one sequence per trial. In the case of the tactile speller there are two sequences per trial (first row selection, then column / character selection).

Stimulus General term for anything that appears on the screen.

Stimulus event Single change of the stimuli presented on the screen.

Stimulus event accuracy Accuracy with which the classifier is able to determine wether the current target is accentuated or not, based on the brain data.

Stimulus Onset Asynchrony (SOA) Time from the start of one stimulus to the start of the next stimulus, inverse of stimulus rate.

Stimulus pattern The way letters are grouped in accentuation (row-column (RC) or pseudo-random noise (PRN)).

Stimulus rate Speed of accentuation of letters, inverse of SOA.

Stimulus type Type of accentuation (flash or flip).

Subserie Unit within a sequence, consisting of multiple events that can be grouped together. In the visual speller this is corresponds to accentuating all rows and columns once. This is then repeated multiple times to form a sequence.

Target-to-Target Interval (TTI) Time between consecutive accentuations of the target letter.

Time frequency representation (TFR) Data representation that shows frequency changes over time. Time and frequency are on the x-axis and y-axis. Power or amplitude is indicated by color, where red is positive and blue is negative.

Training time Amount of time it takes to collect the data that is used to train the classifier.

Trial Period during which data is gathered to decode a complex intention. Can consist of multiple sequences. In the case of the visual speller, a trial is the decoding of a single character.

Appendix A

Priming stimuli

A.1 Related pairs

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
jazz	0.301	4	1	saxofoon	0	8	2
wasknijper	0	10	3	was	0	3	1
bestek	0.9542	6	2	vork	1.0792	4	1
krik	0	4	1	pech	0.8451	4	1
eiwit	0.9542	5	2	eigeel	0.301	6	2
bezem	0.6021	5	2	heks	0	4	1
dam	0.699	3	1	bever	0	5	2
spinazie	0.4771	8	3	groen	0	5	1
tennisracket	0	12	4	tennisbal	0	9	3
pompelmoes	0	10	3	bitter	0	6	2
walrus	0	6	2	snor	0	4	1
racket	0	6	2	tennis	0.301	6	2
confituur	0	9	3	aardbei	0.699	7	2
periscoop	0	9	3	duikboot	0.301	8	2
vlot	0.4771	4	1	snel	0	4	1
puck	0	4	1	hockey	0	6	2
beroep	2.0453	6	2	werk	2.7566	4	1
volleybal	0	9	3	net	1.2553	3	1
zoogdier	0.7782	8	2	mens	0	4	1
libel	0	5	2	vijver	1.1761	6	2
naald	1.2041	5	1	draad	1.4472	5	1
spek	0	4	1	varken	1.3617	6	2
mier	0.8451	4	1	klein	0.301	5	1
tol	0.699	3	1	speelgoed	1.1461	9	2
pak	1.7853	3	1	kostuum	1.0792	7	2
vet	1.1761	3	1	dik	0	3	1
inbraak	0.6021	7	2	dief	1.1139	4	1
zwaard	1.1761	6	1	ridder	1.1139	6	2
aambeeld	0	8	2	smid	0.7782	4	1
puzzel	0.6021	6	2	stukje	1.9494	6	2
zakdoek	1.3222	7	2	snuit	0.7782	5	1

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
ton	1.4771	3	1	vat	0.699	3	1
verjaardag	1.3222	10	3	cadeau	1.3424	6	2
vampier	0.6021	7	2	bloed	0	5	1
roofvogel	0.301	9	3	arend	0.6021	5	2
gewei	0	5	2	hert	0.8451	4	1
denneappel	0	10	4	bos	0.301	3	1
web	0.6021	3	1	spin	0.9542	4	1
balkon	1.2304	6	2	terras	1.6128	6	2
rups	0	4	1	vlinder	1	7	2
kapstok	0.699	7	2	jas	0	3	1
moer	0.4771	4	1	vijs	0	4	1
hazelnoot	0	9	3	eekhoorn	0.4771	8	2
wei	1.0414	3	1	koe	1.5563	3	1
punt	1.2553	4	1	komma	0.4771	5	2
tram	1.301	4	1	spoor	0.4771	5	1
tweeloop	0	8	2	geweer	1.6628	6	2
riek	0	4	1	hooi	0.8451	4	1
artisjok	0	8	3	groente	1.3617	7	2
notenbalk	0	9	3	muziek	2.0607	6	2
mei	1.7924	3	1	lente	1.2788	5	2
bruid	1.0414	5	1	bruidegom	0.699	9	3
dolfijn	0.6021	7	2	flipper	0	7	2
goal	0.301	4	1	voetbal	0	7	2
slip	0.6021	4	1	ondergoed	0.9542	9	3
harpoen	0	7	2	walvis	0.4771	6	2
aas	0.301	3	1	worm	1	4	1
clementine	0	10	4	mandarijn	0.4771	9	3
wittekool	0	9	3	rodekool	0	8	3
prehistorie	0	11	4	oermens	0	7	2
tekenfilm	0	9	3	cartoon	0	7	2
ijshockey	0	9	3	schaats	0	7	1
pasta	0.4771	5	2	spaghetti	0.4771	9	3
ooievaar	0.301	8	3	nest	1.3802	4	1
kuif	0.4771	4	1	gel	0	3	1
kurk	0	4	1	fles	2.0492	4	1
masker	1.2553	6	2	carnaval	0.4771	8	3
raam	2.2405	4	1	venster	1.4624	7	2
rasp	0	4	1	wortel	1.5682	6	2
zilver	1.0792	6	2	juweel	1.1139	6	2
muizeval	0	8	3	muis	1.3222	4	1
eiland	1.8921	6	2	palmboom	0.4771	8	2
molen	1.0414	5	2	wiek	0.4771	4	1
stekker	0.301	7	2	stopcontact	0.301	11	3
neushoorn	0	9	2	grijs	0.699	5	1
giraf	0	5	2	vlek	0	4	1
theepot	0.301	7	2	thee	0	4	1
kalkoen	0.4771	7	2	kerstmis	0	8	2
strijkplank	0	11	2	strijkijzer	0	11	3

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
rugbybal	0	8	3	ovaal	0	5	2
leguaan	0	7	3	reptiel	0.4771	7	2
badminton	0	9	3	pluimpje	0	8	2
ochtend	1.9031	7	2	moe	0.6021	3	1
inktvis	0.301	7	2	tentakel	0	8	3
fanfare	0.4771	7	3	trompet	0.6021	7	2
jungle	0.699	6	2	oerwoud	1	7	2
triangel	0	8	3	driehoek	0.9542	8	2
pijp	1.3979	4	1	tabak	1.1139	5	2
doedelzak	0	9	3	schot	0.4771	5	1
kameel	0.8451	6	2	bult	0.6021	4	1
slurf	0	5	1	olifant	1	7	3
klok	1.5682	4	1	wijzer	0.6021	6	2
ezel	1.0792	4	2	dom	0.301	3	1
wandelstok	0.699	10	3	oud	0.4771	3	1
brand	1.6532	5	1	brandweer	0.6021	9	2
goudvis	0.301	7	2	bokaal	0.301	6	2
vlaai	0	5	1	taart	1	5	1
bat	0	3	1	honkbal	0	7	2
ansjovis	0.301	8	3	pizza	0	5	2
ijsje	0.4771	5	2	vanille	0.301	7	3
boormachine	0	11	4	lawaai	1.4914	6	2
vuilbak	0	7	2	afval	1.1139	5	2
engel	1.415	5	2	hemel	0.301	5	2
orkest	1.0414	6	2	dirigent	0.8451	8	3
dorst	1.1461	5	1	drinken	1.699	7	2
kaaiman	0	7	2	krokodil	0.699	8	3
krokus	0	6	2	vakantie	1.7404	8	3
wafel	0.301	5	2	slagroom	0.6021	8	2
luier	0.8451	5	2	baby	1.8976	4	2
noordpool	0.301	9	2	zuidpool	0.301	8	2
gebak	0.6021	5	2	cake	0.4771	4	1
loodgieter	0.301	10	3	buis	0.9031	4	1
sinterklaas	0.6021	11	3	zwartepiet	0	10	3
kerstman	0	8	2	kerstboom	0.699	9	2
ballet	0.6021	6	2	roze	0.301	4	2
stewardess	0.4771	10	3	vliegtuig	1.716	9	2
puree	0.301	5	2	aardappel	1.4472	9	3
kwark	0.301	5	1	yoghurt	0.4771	7	2
geur	1.8451	4	1	parfum	1.1761	6	2
amfibie	0	7	3	kikker	0.9542	6	2
ring	1.5315	4	1	trouw	0	5	1
beha	0.699	4	2	borst	0	5	1
statief	0	7	2	fototoestel	0.6021	11	4
scharnier	0.4771	9	2	piep	0	4	1
tandarts	1.1139	8	2	pijn	2.1847	4	1
tandenborstel	0.6021	13	4	tandpasta	0.4771	9	3
boks	0	4	1	handschoen	1.1139	10	2

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
sinaasappel	0.9031	11	4	oranje	0.7782	6	3
gereedschap	1.0414	11	3	hamer	1.0414	5	2
keu	0	3	1	biljart	0	7	2
schaar	0	6	1	knip	0	4	1
skelet	0.699	6	2	geraamte	0.699	8	3
druk	1.9868	4	1	stress	1.0792	6	1
kruk	0.9542	4	1	bar	0	3	1
rolschaats	0	10	2	val	0	3	1
muur	0	4	1	baksteen	0.699	8	2
keukengerief	0	12	4	lepel	1.2553	5	2
fabriek	1.6435	7	2	arbeider	1.7853	8	3
tankstation	0	11	4	benzine	0.9542	7	3
zondag	1.6128	6	2	weekend	1.2304	7	2
kievit	0.301	6	2	vogel	1.9823	5	2
fagot	0	5	2	instrument	1.6812	10	3
kok	0	3	1	muts	0.8451	4	1
chips	0.6021	5	1	paprika	0.699	7	3
autosnelweg	0	11	4	file	0.4771	4	1
assepoester	0	11	4	sprookje	1.2041	8	2
badkamer	1.3802	8	3	bad	1.3802	3	1
lava	0.301	4	2	vulkaan	0.7782	7	2
aubergine	0.301	9	3	paars	0.4771	5	1
zoet	0	4	1	snoep	0.301	5	1
ruw	0	3	1	schuurpapier	0	12	3
kano	0.699	4	2	varen	0.4771	5	2
metaal	0	6	2	ijzer	1.2553	5	2
drank	1.5911	5	1	cola	0.699	4	2
vijl	0	4	1	nagel	1.3424	5	2
oliebol	0	7	3	kermis	1.0414	6	2
pauw	0.7782	4	1	veer	1.1461	4	1
waterput	0.301	8	3	emmer	1.3424	5	2
camping	0.4771	7	2	caravan	0.6021	7	3
brievenbus	0.7782	10	3	post	1	4	1
vrede	1.716	5	2	duif	0	4	1
croissant	0.301	9	2	ontbijt	1.4314	7	2
rechtbank	1.3802	9	2	advocaat	1.4914	8	3
magie	1.0414	5	2	tovenaar	0.8451	8	3
bok	0	3	1	geit	0.301	4	1
judo	0	4	2	mat	0.8451	3	1
vijg	0	4	1	plat	0	4	1
plan	2.3032	4	1	idee	0.8451	4	2
dinosaurus	0	10	4	groot	0	5	1
pull	0	4	1	trui	0	4	1
egel	0.4771	4	2	stekel	0.4771	6	2
hak	0	3	1	schoen	1.8325	6	1
hark	0.301	4	1	tuin	2.0755	4	1
paperclip	0	9	3	papier	2.0531	6	2
wol	1	3	1	schaap	1.415	6	1

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
bed	2.4771	3	1	slaap	0.4771	5	1
rad	0.9031	3	1	fortuin	0.9031	7	2
kleerkast	0.6021	9	2	kleren	1.6335	6	2
boete	0.9542	5	2	politie	1.9777	7	3
boter	1.3617	5	2	boterham	1.2553	8	3
thermometer	0.4771	11	4	koorts	1.3424	6	1
paddestoel	0.9542	10	3	kabouter	0.699	8	3
chocolade	0.699	9	4	bruin	0	5	1
snaar	0.699	5	1	gitaar	0.7782	6	2
synthesizer	0	11	4	piano	1.2041	5	3
brandweerwagen	0	14	4	sirene	1	6	3
palet	0	5	2	schilder	1.4472	8	2
moto	0	4	2	snelheid	1.6021	8	2
apotheker	0.9031	9	4	medicijn	1.415	8	3
cel	1.6628	3	1	gevangenis	1.6335	10	4
deksel	1.2553	6	2	pot	0.699	3	1
winkelbediende	0	14	5	kassa	0.8451	5	2
toneel	1.5441	6	2	acteur	1.2553	6	2
safari	0	6	3	jeep	1	4	1
weegschaal	0.699	10	2	gewicht	1.6232	7	2
oudheid	1.1139	7	2	geschiedenis	2.1367	12	4
angel	0.699	5	2	wesp	0.6021	4	1
mango	0	5	2	fruit	1.1139	5	1
veiligheidsspeld	0	16	4	prik	0.4771	4	1
circus	0.8451	6	2	clown	0.699	5	1

A.2 Unrelated pairs

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
vink	0.301	4	1	turkoois	0	8	2
hovercraft	0	10	3	los	0	3	1
rugzak	0.9031	6	2	ford	1	4	1
kort	0	4	1	lens	0.7782	4	1
dieet	1.0414	5	2	mimiek	0.301	6	2
merel	0.699	5	2	flip	0	4	1
dolk	0.699	4	1	lager	0	5	2
spinneweb	0.4771	9	3	bruis	0	5	1
tafeltennis	0	11	4	geknabbel	0	9	3
stekelbaars	0	11	3	gebalk	0	6	2
sweater	0	7	2	vaak	0	4	1
hamster	0	7	2	antiek	0.301	6	2
herbivoor	0	9	3	wroeging	0.699	8	2
kokosnoot	0	9	3	huifkar	0.301	7	2
jacht	0.4771	5	1	fret	0	4	1

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
rog	0	3	1	maaier	0	6	2
gevaar	2.0645	6	2	zaak	2.6274	4	1
supporter	0	9	3	wolf	1.2304	4	1
knuppel	0.7782	7	2	smul	0	4	1
eland	0	5	2	eerbied	1.2041	7	2
haan	1.2304	4	1	laars	1.4314	5	1
meer	0	4	1	verkoop	1.3222	7	2
koek	0.9542	4	1	sloop	0.301	5	1
tang	0.699	4	1	opbrengst	1.2041	9	2
berg	1.7404	4	1	drankje	1.0414	7	2
tank	1.2304	4	1	kul	0	3	1
cocktail	0.6021	8	2	vonk	1.0414	4	1
kraan	1.1461	5	1	kachel	1.1761	6	2
knuffel	0	7	2	hasj	0.699	4	1
handtas	0.6021	7	2	morgen	2.0334	6	2
mantel	1.2553	6	2	zwijn	0.7782	5	1
blok	1.5441	4	1	juf	0.699	3	1
vrachtwagen	1.301	11	3	drukte	1.2553	6	2
magneet	0.4771	7	2	plint	0	5	1
hamburger	0.301	9	3	sage	0.699	4	2
lychee	0	6	2	roem	0.9542	4	1
madeliefje	0	10	4	pub	0.4771	3	1
prei	0.6021	4	1	krul	1.0792	4	1
piloot	1.2041	6	2	planeet	1.4914	7	2
pit	0	3	1	ontzag	1	6	2
haring	0.699	6	2	mars	0	4	1
kan	0.4771	3	1	sjiek	0	5	1
breekijzer	0	10	3	geschut	0.4771	7	2
sap	1.0414	3	1	cent	1.415	4	1
kar	1.2041	3	1	galop	0.6021	5	2
hoorn	1.3424	5	1	junk	0.4771	4	1
eenhoorn	0	8	2	vertrek	1.8062	7	2
poef	0	4	1	box	0.699	3	1
bazooka	0	7	3	lengte	1.4314	6	2
rabarber	0	8	3	begrip	2.2201	6	2
golf	1.7853	4	1	leugen	1.3979	6	2
zwaan	0.9031	5	1	levering	0.699	8	3
zwaluw	0.699	6	2	draagtas	0	8	2
biet	0.4771	4	1	spikkel	0	7	2
gesp	0.4771	4	1	reflectie	0.7782	9	3
aalbes	0	6	2	extreem	0.301	7	2
harp	0.301	4	1	goot	0.7782	4	1
dromedaris	0	10	4	visserij	0.699	8	3
luchtballon	0	11	3	decadent	0	8	3
accordeon	0	9	4	turnles	0	7	2
verfborstel	0	11	3	snotaap	0	7	2
microgolf	0	9	3	blaas	0	5	1
bamboe	0.301	6	2	metselaar	0.4771	9	3

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
elastiek	0.4771	8	3	gek	1.3617	3	1
ros	0.301	3	1	dol	0	3	1
slee	0	4	1	strijd	2.0828	6	1
matroos	1.1461	7	2	verliezer	0.6021	9	3
hart	2.2788	4	1	thema	1.4914	5	2
roest	0	5	1	procent	1.7709	7	2
beker	1.1761	5	2	versie	1.3222	6	2
basketbal	0	9	3	stier	1.1139	5	1
natuur	1.9685	6	2	cipier	0.4771	6	2
anker	0.9542	5	2	claxon	0.4771	6	1
pudding	0.4771	7	2	schemerlamp	0.4771	11	3
luipaard	0	8	2	speech	0.4771	6	1
koevoet	0	7	2	aal	0	3	1
topje	0.301	5	2	stamp	0	5	1
kever	0.4771	5	2	fietsband	0	9	2
stinkdier	0	9	2	grootbedrijf	0	12	3
appelflap	0	9	3	duo	0	3	2
hazelworm	0	9	3	duiker	0.4771	6	2
vingerhoed	0	10	3	bloedgroep	0	10	2
geweld	1.7559	6	2	zaag	0.4771	4	1
fazant	0.4771	6	2	regenpijp	0	9	3
kanarie	0.4771	7	3	klavier	0.301	7	2
kampvuur	0.6021	8	2	schotel	1.1139	7	2
plamuurmes	0	10	3	eetzaal	0.8451	7	2
lamp	1.4914	4	1	serie	1.415	5	2
pistolet	0	8	3	staaf	0.7782	5	1
tijger	0.8451	6	2	lei	0.301	3	1
vest	0	4	1	uitstapje	0.8451	9	3
struik	1.4771	6	1	hefboom	0.4771	7	2
ober	1.1461	4	2	buil	0	4	1
postzegel	0.699	9	3	truck	0.301	5	1
pad	1.7709	3	1	waakhond	0.4771	8	2
oorbel	0.301	6	2	knielap	0	7	2
squash	0	6	1	cape	0.699	4	1
kruis	0	5	1	frisdrank	0	9	2
rijbewijs	0.4771	9	3	kookwas	0	7	2
toeter	0.301	6	2	foltering	0.301	9	3
onderlegger	0	11	4	leraar	1.8633	6	2
blokfluit	0	9	2	ego	1.1761	3	2
akker	1.2041	5	2	zitvlak	0.301	7	2
training	1.2553	8	2	prestige	0.8451	8	3
bijl	1.0414	4	1	herstel	1.3617	7	2
oorworm	0	7	2	beschutting	0.699	11	3
klaproos	0	8	2	werkgever	1.4771	9	3
bizon	0	5	2	software	0.4771	8	2
hobby	0.7782	5	2	voedsel	1.8195	7	2
roomsoes	0	8	2	doodskop	0.301	8	2
toga	0.301	4	2	shot	0.4771	4	1

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
bloedzuiger	0	11	3	berm	0.8451	4	1
kruiwagen	0.699	9	3	versiersel	0.301	10	3
glijbaan	0	8	2	sprinkhaan	0.301	10	2
deurknop	0.6021	8	2	piste	0	5	2
wasmachine	0.4771	10	4	landschap	1.6721	9	2
schommel	0.301	8	2	grootvader	1.5315	10	3
snoek	0.301	5	1	autobus	0.4771	7	3
vuist	1.5682	5	1	toerist	1.3424	7	2
contrabas	0	9	3	wolkje	0.6021	6	2
jurk	1.6232	4	1	timer	0	5	2
pony	0.6021	4	2	ijzel	0	5	2
plastiek	0	8	2	verspilling	0.6021	11	3
bromfiets	0.4771	9	2	papje	0	5	2
vloeistof	1.1139	9	2	orde	2.2014	4	2
verrekijker	0.7782	11	4	beroemdheid	0.6021	11	3
step	0	4	1	verwijzing	1.2553	10	3
portefeuille	1.0414	12	4	nadenken	1.0792	8	3
revolver	1.1761	8	3	jurist	0.9542	6	2
orka	0	4	2	aardas	0	6	2
slijper	0	7	2	broos	0	5	1
fornuis	0.699	7	2	isolatie	0.6021	8	4
lijn	2.017	4	1	rund	0.699	4	1
kanon	1.0414	5	2	balg	0	4	1
zwempak	0	7	2	zweef	0	5	1
schaaf	0	6	1	loper	0.699	5	2
platenspeler	0	12	4	chip	1.0792	4	1
schrijven	1.8865	9	2	eigenschap	1.7993	10	3
opvoedster	0	10	3	utopie	0.7782	6	3
vleugel	1.5798	7	2	eindpunt	0.7782	8	2
beschuit	0.301	8	2	toekomst	2.1173	8	2
iglo	0	4	2	politicus	1.5315	9	4
rock	0.301	4	1	dun	0.6021	3	1
specht	0.301	6	1	verpleger	0.6021	9	3
klavecimbel	0	11	4	schare	0.4771	6	2
tomatensaus	0	11	4	dienblad	0.699	8	2
psycholoog	1.6128	10	3	vocht	1.2041	5	1
gekko	0	5	2	aardbol	0.4771	7	2
zeehond	0.301	7	2	krot	0.4771	4	1
potvis	0	6	2	bout	0.301	4	1
banjo	0	5	2	verkwikking	0	11	3
paling	0.7782	6	2	geldstuk	0.301	8	2
platvis	0	7	2	cabine	1.0414	6	3
poot	1.6021	4	1	spuit	0.4771	5	1
mot	0.301	3	1	dollar	1.6335	6	2
trombone	0	8	3	commando	1.0414	8	3
gif	0.699	3	1	zusje	1.3617	5	2
draaimolen	0.301	10	3	rondje	0.9031	6	2
forel	0.4771	5	2	agenda	1.0414	6	3

Prime				Probe			
Word	LogFreq	LetCnt	SylCnt	Word	LogFreq	LetCnt	SylCnt
pantoffel	0.699	9	3	robot	0.7782	5	2
knie	1.9243	4	1	rit	0	3	1
trechter	0.301	8	2	tegenzin	1.1761	8	3
priester	1.6628	8	2	voldoening	1.2304	10	3
vlieger	0.7782	7	2	casino	1.1139	6	3
micro	0	5	2	teddy	0.301	5	2
lolly	0	5	2	album	0.6021	5	2
ajuin	0	5	2	krukas	0	6	2
geluid	2.1644	6	2	made	0.6021	4	2
piranha	0	7	3	drum	0	4	1
stop	0.301	4	1	dadel	0	5	2
kiwi	0.301	4	2	oogvocht	0	8	2
wok	0.301	3	1	leiding	1.8573	7	2
hoef	0.301	4	1	produkt	1.9345	7	2
basgitaar	0	9	3	stadium	1.6532	7	3
mus	1.2553	3	1	contract	1.3222	8	2
kant	2.4639	4	1	slaapzak	0.6021	8	2
vlo	0.6021	3	1	hoofdpijn	1.301	9	2
sandwich	0.4771	8	2	instituut	1.4624	9	3
zalm	0.699	4	1	ambtenaar	1.7634	9	3
worst	1.0414	5	1	opluchting	1.2553	10	3
kinderwagen	0.6021	11	4	vracht	0.699	6	1
hagedis	0.7782	7	3	kleinkind	0.9031	9	2
aquarium	0.699	8	4	roeispaan	0	9	2
uil	0.9031	3	1	omhulsel	0.4771	8	3
marktkramer	0	11	3	tasje	0.8451	5	2
schommelstoel	0.301	13	3	symfonie	0.699	8	3
krekel	0.4771	6	2	schoonheid	1.6435	10	2
koala	0	5	3	vernieuwing	1.415	11	3
viooltje	0.4771	8	3	bestemming	1.3424	10	3
gordijn	1.6532	7	2	geneesmiddel	1.3979	12	4
viool	1.0792	5	2	kauw	0	4	1
cassetterecorder	0	16	6	opvoeder	0.8451	8	3
koningin	1.6128	8	3	herhaling	1.2788	9	3
kameleon	0	8	4	dia	0.6021	3	2
ekster	0.4771	6	2	tijdschrift	1.5911	11	2
fluit	0.699	5	1	psychologie	1.7993	11	4
wekker	0.8451	6	2	sabbat	0	6	2
perzik	0	6	2	bont	0.301	4	1
verkeerslicht	0.301	13	3	kers	0	4	1
tomaat	0.9542	6	2	nectar	0	6	2

Appendix B

Semantic relation stimuli

B.1 Training stimuli

Prime	Related probes	Unrelated probes
auto	krik, stuur, garage, rijbewijs, gordel	trouw, rugvin, postpakket, framboos, getuigenis, flatgebouw, breigoed, balletschoen, geluksdag, kruisbeeld
baby	luier, kinderbed, kinderwagen, kinderstoel, ooievaar	praatje, ziel, kobbe, dansvloer, rijweg, reggae, stopteken, belg, hagel, vervuiling
bakker	pistolet, croissant, brood, roomsoes, appelflap	presentatie, schoensmeer, kelp, borduursel, reflex, bles, vacature, ribbe, trom, kookplaat
bal	rugby, rond, tafeltennis, pingpong, squash	geduld, mongool, stofwolk, giraffe, kaliber, garde, notitieboekje, afwas, berging, restaurant
blauw	lucht, politie, jeans, politieagent, hemel	beestje, scherf, pastoor, voorschoot, krulhaar, straatmuziek, telefoonkabel, vitrine, slaap, sax
bloem	margriet, vaas, iris, tulp, orchidee	filter, reu, mop, golfstok, strikje, vervuiling, paling, hal, plas, kwal
boom	bos, specht, blad, tak, hout	zoutvat, turntoestel, hitte, conservenblik, krant, huifkar, neerhof, kolonist, schrijfgerei, ruimteschip
boot	anker, schip, hovercraft, varen, vaartuig	handbeweging, arbeid, wandelpad, ijshockey, karwei, vezel, crisis, buste, gereedschap, gasvuur
bos	denneappel, hert, boom, vos, paddestoel	delinquent, rouw, video, doek, praal, slurf, bombardement, horrorfilm, weg, verstand
brief	postzegel, enveloppe, post, brievenbus, postbode	blind, smog, kop, stro, reus, buschauffeur, muntje, hoepel, ingenieur, kunststof
broek	riem, gesp, jeans, rits, kleding	trom, code, oorveeg, spelling, langpootmug, ringetje, jojo, explosief, inlegzool, latex
deur	sleutel, scharnier, klink, deurknop, slot	associatie, springbok, lichaamscel, lappendeken, smaak, tijdmachine, etalagepop, sufferd, opvoeding, platina
dier	poot, staart, gekko, lama, hert	schel, venijn, kenteken, beschermer, zwavel, doelstelling, berging, boef, oneindigheid, kerk
drinken	dorst, glas, bier, vloeistof, water	afloop, beschadiging, walging, tennis, interpretatie, les, grime, vacature, huiskamer, teddybeer
ei	kuiken, kip, spek, struisvogel, omelet	onwetendheid, zonnebloempit, boerenpaard, scheenbeen, borstel, observatie, haar, brie, duvel, bloemenwinkel
eten	keuken, kok, restaurant, microgolf, tafel	postwagen, gevangene, zwaluwnest, chef, vervoeging, postkaart, rugleuning, radio, dragon, speldekop
fiets	tandem, postbode, zadel, vervoer, wiel	stilleven, schmink, pinda, shampoo, stoelgang, illegaal, cruise, gedicht, chocoladetaart, vlaai

Prime	Related probes	Unrelated probes
fruit	sap, appel, peer, perzik, mango	vaccin, sabel, buideldier, loop, koper, laars, grill, singel, smeerkaas, zondag
geel	pudding, parkiet, ananas, kanarie, kaas	blijde, zomervakantie, weemoed, wijze, buffel, tomahawk, chirurgie, levensritme, tooi, sporter
geld	kassa, portefeuille, spaarvarken, portemonnee, kluis	augurk, opener, departement, kar, keyboard, rolschaatsbaan, kunststijl, uitloop, spionage, sereniteit
gitaar	banjo, snaar, rock, straatmuzikant, muziekinstrument	papaver, schrijfmap, ceintuur, kerstboom, schaafwond, kruisteken, brievenbus, keukengerei, verbeelding, scout
gras	tuin, groen, grasmachine, weide, wei	credit, openheid, menseneter, zool, brievenbus, proefje, thuis, salami, golfbeweging, zitkamer
groen	kikker, gras, kiwi, spinazie, komkommer	klimop, vinger, practicum, volwassenheid, lans, hel, punk, impasse, meter, stormram
groente	selderij, aubergine, artisjok, venkel, wittekool	havenwerker, functie, beeld, twist, erfenis, beenhouwer, vergroting, schoolbank, wetgeving, flanel
groot	klein, dinosaurus, reus, olifant, walvis	planner, klank, industrie, prestatie, speelkaart, buidel, badhanddoek, foetsie, meet, onderzoeksinstrument
haar	luis, kuif, hoofd, pruik, kam	niet, klikker, manager, hijs, werkman, nicht, deeg, uier, ontsmettingsmiddel, ara
hout	zaag, plank, splinter, schaaf, boom	tikmachine, delicatesse, loempia, mosterd, grind, tortel, puntschoen, slotenmaker, garagepoort, marktplaats
kaas	muizeval, gat, rasp, geel, sandwich	koffieboon, rendement, lied, zandplaat, geschiedenisles, dokwerker, schoolslag, koude, vereniging, vrieskou
kind	opvoedster, speeltuin, tekenfilm, schommel, draaimolen	bruidstaart, racepaard, schrijfkamer, ruiten, klapband, overjas, aanwezigheid, zeester, rest, hak
klein	mier, microscoop, pony, hamster, groot	schadevergoeding, innerlijk, strijkbout, vuilemmer, roet, gemoedstoestand, petitie, poedel, hijskraan, denim
kleur	paars, kameleon, papegaai, blauw, regenboog	scheikunde, tel, puppy, vlam, flair, elektronica, mijnwerker, gemiauw, loon, toeverlaat
licht	pluimpje, vuurtoren, lamp, schakelaar, zaklamp	wind, gracht, kopstoot, volwassenheid, mergbeen, paleontoloog, aannemer, klaagzang, sjorring, visserij
muis	muizeval, kaas, rat, kat, grijs	slijtage, drietand, wegaanduiding, wijs, funk, ketelmuziek, mogelijkheid, scout, hoorn, biljart
muziek	banjo, notenbalk, synthesizer, ritme, tamboerijn	papa, voorbeeld, emancipatie, zonneschijn, treffen, kleurverandering, strook, hitte, verstopping, natrium
oorlog	soldaat, tank, granaat, vrede, bazooka	smash, avontuur, vislijm, aardbeving, rijder, raad, rappel, plakker, hengst, ven
oranje	pompoen, clementine, sinaasappel, abrikoos, wortel	kristal, spriet, weidsheid, literatuur, prei, adem, evenbeeld, nevel, greep, medaillon

B.2 Online stimuli

Prime	Related probes	# Probes
wit	wit, zwart, kleur, licht, brood, ei	6
eten	eten, vis, geur, winkel, keuken, pot, oma, vlees, groente, restaurant, schort, tafel, veel, drinken, soep, wild, ei, noot	18
rood	rood, groen, geel, kleur, blauw, bloed, vuur, liefde, vlees, roze, roos	11
zwart	wit, zwart, kleur, dood, grijs, donker, vlieg, hoed, leer, kat	10
water	water, blauw, zee, plant, drinken, nat, plat	7
groot	groot, klein, man, paard, veel	5
groen	rood, groen, kleur, boom, tuin, natuur, gras, plant, oranje, groente, veld	11
zomer	zomer, vakantie, zon, zee, winter, vlieg, fruit, strand	8
pijn	pijn, bloed, vuur, tand, scherp	5
bruin	bruin, boom, hout, haar, paard, grond, kast, noot	8
klein	groot, klein, kind, vlieg	4
werk	werk, saai, geld, schort, beroep, werktuig	6
dier	dier, natuur, bos, mens, hond, paard, vlees, kat, wild	9
kind	klein, kind, man, spel, vrouw, mens, moeder, bescherming, step	9
vakantie	zomer, vakantie, zon, zee, boek, reis, zand, strand	8
geel	rood, geel, kleur, blauw, zon, oranje, licht, bus, kaas	9
kleur	wit, rood, zwart, groen, geel, kleur, blauw, bloem, haar, oranje, roze, roos	12
boom	groen, bruin, boom, hout, tuin, natuur, bos, wind, blad, stok, noot	11
blauw	rood, water, geel, kleur, blauw, zee, lucht, aarde, oog, politie	10
rond	rond, dik, bal, voetbal	4
lawaai	lawaai, geluid	2
vuil	vuil, stof, schort, was	4
hout	bruin, boom, hout, bos, vuur, fluit, stok, kast	8
tuin	groen, boom, tuin, zon, gras, bloem, plant, werktuig	8
natuur	groen, dier, boom, natuur, bos, gras, bloem, plant, berg	9
man	groot, kind, man, vrouw, mens	5
school	school, saai, boek, leer, dom, vriend, bus	7
zon	zomer, vakantie, geel, tuin, zon, zee, reis, zand, licht, strand	10
dood	zwart, dood	2
spel	kind, spel, voetbal, plezier, vriend	5
auto	auto, gevaar, snel, duur, weg, band, snelheid	7
zee	water, zomer, vakantie, blauw, zon, zee, vis, reis, zand, boot, nat, land, strand	13
oud	oud, grijs, oma, hoed	4
bos	dier, boom, hout, natuur, bos, blad, stok, wild, konijn	9
saai	werk, school, saai	3
film	film	1
grijs	zwart, oud, grijs, ijzer, metaal, haar, steen, donker, oma	9
vrouw	kind, man, vrouw, moeder, meisje	5
ijzer	grijs, ijzer, metaal	3
geld	werk, geld, winkel, veel, beroep	5
vis	eten, zee, vis, stank	4
gevaar	auto, gevaar	2
huis	huis, steen	2
geluid	lawaai, geluid	2

Prime	Related probes	# Probes
muziek	muziek, feest, dans, noot	4
gras	groen, tuin, natuur, gras, grond, veld, voetbal	7
lief	lief, oma, vriend, meisje, konijn	5
snel	auto, snel	2
feest	muziek, feest, drank, dans, plezier, vriend	6
mens	dier, kind, man, mens, veel	5
metaal	grijs, ijzer, metaal	3
geur	eten, geur, bloem, stank, roos	5
bloem	kleur, tuin, natuur, geur, bloem, plant, pot, veld, roze, roos	10
duur	auto, duur, restaurant, kleding	4
stank	vis, geur, stank	3
winkel	eten, geld, winkel, zak	4
dik	rond, dik	2
stof	vuil, stof, kleding	3
fiets	fiets, band, step	3
plant	water, groen, tuin, natuur, bloem, plant, pot, blad	8
bloed	rood, pijn, bloed, vlees	4
haar	bruin, kleur, grijs, haar	4
hond	dier, hond, vriend, kat, stok	5
boek	vakantie, school, boek	3
sport	sport, voetbal	2
keuken	eten, keuken, pot, schort, tafel	5
paard	groot, bruin, dier, paard	4
steen	grijs, huis, steen, grond, berg	5
vogel	vogel, lucht, vlieg, ei	4
lucht	blauw, vogel, lucht, wind	4
pot	eten, bloem, plant, keuken, pot	5
winter	zomer, winter, donker, ijs, soep	5
donker	zwart, grijs, winter, donker, licht, gat, middeleeuwen	7
reis	vakantie, zon, zee, reis, weg, strand	6
zand	vakantie, zon, zee, zand, strand	5
oranje	groen, geel, kleur, oranje	4
oma	eten, oud, grijs, lief, oma	5
grond	bruin, gras, steen, grond, gat, aarde, land	7
vlieg	zwart, zomer, klein, vogel, vlieg	5
vuur	rood, pijn, hout, vuur	4
licht	wit, geel, zon, donker, licht	5
gat	donker, grond, gat, kaas	4
berg	natuur, steen, berg, veel	4
hoed	zwart, oud, hoed	3
liefde	rood, liefde, moeder, vriend, roos	5
wind	boom, lucht, wind, regen	4
bal	rond, bal, voetbal, soep	4
drank	feest, drank, glas	3
vlees	eten, rood, dier, bloed, vlees	5
groente	eten, groen, groente, soep, fruit	5
moeder	kind, vrouw, liefde, moeder, schort, bescherming, was	7
veld	groen, gras, bloem, veld, voetbal, boer	6
voetbal	rond, spel, gras, sport, bal, veld, voetbal	7

Prime	Related probes	# Probes
blad	boom, bos, plant, blad	4
tand	pijn, tand, konijn	3
weg	auto, reis, weg	3
boot	zee, boot	2
dans	muziek, feest, dans, plezier	4
plezier	spel, feest, dans, plezier	4
restaurant	eten, duur, restaurant, drinken	4
leer	zwart, school, leer, schoen	4
band	auto, fiets, band, vriend	4
kleding	duur, stof, kleding	3
schort	eten, werk, vuil, keuken, moeder, schort	6
aarde	blauw, grond, aarde	3
dom	school, dom	2
regen	wind, regen, nat	3
roze	rood, kleur, bloem, roze, meisje, roos	6
schoen	leer, schoen	2
brood	wit, brood, kaas	3
ijs	winter, ijs	2
scherp	pijn, scherp, glas	3
tafel	eten, keuken, tafel, kast	4
vriend	school, spel, lief, feest, hond, liefde, band, vriend	8
kat	zwart, dier, hond, kat	4
veel	eten, groot, geld, mens, berg, veel	6
bescherming	kind, moeder, bescherming	3
boer	veld, boer	2
drinken	eten, water, restaurant, drinken, glas	5
meisje	vrouw, lief, roze, meisje	4
nat	water, zee, regen, nat	4
oog	blauw, oog	2
roos	rood, kleur, geur, bloem, liefde, roze, roos	7
step	kind, fiets, step	3
hand	hand	1
plat	water, plat	2
soep	eten, winter, bal, groente, soep	5
beroep	werk, geld, beroep	3
fluit	hout, fluit, noot	3
stok	boom, hout, bos, hond, stok	5
wild	eten, dier, bos, wild	4
bus	geel, school, bus	3
fruit	zomer, groente, fruit	3
glas	drank, scherp, drinken, glas	4
kerk	kerk	1
middeleeuwen	donker, middeleeuwen	2
ei	wit, eten, vogel, ei	4
konijn	bos, lief, tand, konijn	4
land	zee, grond, land	3
zak	winkel, zak	2
kast	bruin, hout, tafel, kast	4
noot	eten, bruin, boom, muziek, fluit, noot	6

Prime	Related probes	# Probes
snelheid	auto, snelheid	2
politie	blauw, politie	2
was	vuil, moeder, was	3
zoet	zoet, suiker	2
kaas	geel, gat, brood, kaas	4
strand	zomer, vakantie, zon, zee, reis, zand, strand	7
suiker	zoet, suiker	2
werktuig	werk, tuin, werktuig	3

B.3 Post-training stimuli

Prime	Related probes	Unrelated probes
paard	zadel, ruiter, ros, koets, manen	selectie, zeelucht, nicht, inlegzool, index, clochard, namiddag, bekendheid, sluwigheid, handenarbeid
pijn	tandarts, zweep, splinter, verdriet, wond	antwoord, hogeschool, medelijden, moment, mongool, tijdrit, oogschaduw, gezicht, onderverdeling, titanium
regen	nat, regenboog, paraplu, worm, wolk	item, kauw, erwt, gommetje, goliath, speelster, geluid, droefheid, pils, hijs
rijst	wok, paella, kip, wit, eten	kempen, funk, uniform, grind, trainer, tentzeil, bezinning, kruimel, zwijgen, reukorgaan
rood	lippenstift, tomaat, grenadine, klaproos, verkeerslicht	gigant, gymnasium, hasj, laurier, zuid, bloemist, stumperd, sprei, eindpunt, haarborstel
rook	brand, sigaret, tabak, sigaar, schoorsteen	overjas, meetlint, mestkever, citrusvrucht, snijmes, glaswerk, zadeldak, schaaf, bewerking, windwijzer
sneeuw	muts, slede, wit, winter, sneeuwman	huid, wasverzachter, luchtgat, schoorsteenveger, scheldpartij, grasmat, platenspeler, put, object, gerechtszaal
sport	doping, rugby, volleybal, rugbybal, polo	politica, blijdschap, naaldhak, libel, kippenhok, damesschoen, mestkever, trombose, dansvloer, verzekering
stank	ui, stinkdier, vuilbak, vuilniskar, asbak	schok, knaagtand, graat, koffiezetapparaat, atoomreactor, kinderafdeling, tongzoen, stapelplaats, woonwagen, papier
tand	vampier, piranha, tandpasta, krokodil, tandenborstel	schilderij, voeg, folk, gamma, inbreuk, socialist, handtekening, factuur, kruidnagel, slaapkamer
tuin	hek, kruiwagen, gras, hark, bloem	passievrucht, paardestal, zwavelzuur, luider, opzoeking, route, gerommel, lelijkheid, speeltje, bast
vakantie	tent, caravan, krokus, zomer, fototoestel	els, langoustine, uitschot, koe, rijlaars, springpoot, investering, mummie, merg, maandagavond

Summary

This thesis is about Brain Computer Interfaces (BCIs) for Communication, specifically on how they can be improved. A BCI is a system that allows someone to control a computer by using only their brain activity. One of the best known BCIs for communication is the visual speller, which has first been developed in 1988, and has been researched intensively since then.

Chapter 2 investigated improvements based on different stimulus properties, e.g., speed or pattern of stimulation, within the visual speller as it has first been developed by Farwell and Donchin (1988). Each of the different stimulus properties have been tested in previous literature and have a known effect on visual speller performance. The chapter investigated whether a combination of these types of stimuli can lead to a greater improvement. It was found that higher stimulus rates can improve the visual speller performance and can lead to less time required to train the system. It was also found that a proper stimulus code can overcome the weaker brain response elicited by this code compared to using the Farwell and Donchin (1988) code, but can not greatly improve speller performance.

Some patient groups that would benefit from a communication BCI are not able to direct their eye gaze anymore. Therefore, a tactile speller was developed and compared with existing visual speller paradigms in terms of classification performance and elicited ERPs, this was described in chapter 3. The fingertips of healthy participants were stimulated with short mechanical taps while EEG activity was measured. The letters of the alphabet were allocated to different fingers and subjects could select one of the fingers by silently counting the number of taps on that finger. The offline and online performance of the tactile speller was compared to the overt and covert attention visual matrix speller and the covert attention Hex-o-Spell speller. The chapter shows that it is possible to use a tactile speller for communication. The tactile speller provides a useful alternative to the visual speller, especially for people whose eye gaze is impaired.

Chapter 4 aims at detecting semantic priming at the single-trial level. Priming could be used to traverse a semantic network and determine which word a person has in mind. By using machine learning techniques it is possible to analyse and classify short traces of brain activity, which could, for example, be used to build a Brain Computer

Interface (BCI). The chapter describes an experiment where subjects were presented with word pairs and asked to decide whether the words were related or not. A classifier was trained to determine whether the subjects judged words as related or unrelated based on one second of EEG data. The chapter shows that semantic priming can be detected significantly above chance level for all subjects.

Chapter 5 investigates a possible Brain Computer Interface (BCI) based on semantic relations. As mentioned in the previous paragraph, the semantic relations are used to move through a semantic network.The BCI determines which prime word a subject has in mind by presenting probe words using an intelligent algorithm. Subjects indicate when a presented probe word is related to the prime word by a single finger tap. The detection of the neural signal associated with this movement is used by the BCI to decode the prime word. The movement detector combined both the evoked (ERP) and induced (ERD) responses elicited with the movement. The chapter shows that the intelligent algorithm used to present the probe words has a significantly higher performance than a random selection of probes. Simulations demonstrate that the BCI also works with larger vocabulary sizes, and the performance scales logarithmically with vocabulary size.

This thesis has shown some possible improvements, by using better stimulus encoding, using more appropriate stimulus modalities or trying to detect higher level cognitive concepts. Whilst all of these approaches show some promise, none was the 'silver bullet' which would make useable BCIs a reality. In fact whilst it is clear that patient BCIs will be useful in the next few years, it is also clear that much more work is needed before they represent a viable alternative communication modality for the majority of patients and can be moved out of the lab and into the homes of users in need.

Nederlandse Samenvatting

Dit proefschrift gaat over Brein-Computer Interfaces (BCIs) voor communicatie. Het gaat in het bijzonder over hoe deze systemen verbeterd kunnen worden. Een BCI is een systeem dat iemand in staat stelt een computer te besturen door alleen gebruik te maken van hersenactiviteit. Eén van de bekendste BCIs voor communicatie is de visuele speller. De visuele speller is voor het eerst ontwikkeld in 1988 en er is sinds die tijd veel onderzoek naar gedaan.

Hoofdstuk 2 beschrijft onderzoek naar verbetering gebaseerd op verschillende eigenschappen van de stimuli die gebruikt worden in de visuele speller zoals deze als eerste is ontwikkeld door Farwell and Donchin (1988). Elke stimuluseigenschap is al in eerder onderzoek bestudeerd en ze hebben een bekend effect op de prestatie van de visuele speller. Dit hoofdstuk onderzoekt of er een verbetering optreedt bij een combinatie van deze eigenschappen. Er werd aangetoond dat een hogere snelheid in het aanbieden van stimuli de prestatie van de visuele speller kan verbeteren en leidt tot een kortere trainingstijd van het systeem. Er is tevens aangetoond dat een goede stimulus code het zwakkere hersensignaal ten opzichte van de Farwell and Donchin (1988) code kan compenseren, maar de prestatie neemt niet in grote mate toe.

Sommige groepen patiënten zijn niet meer in staat hun ogen te richten. Voor deze groep patiënten is er een tactiele speller ontwikkeld. Deze ontwikkeling wordt beschreven in hoofdstuk 3. De tactiele speller wordt vergeleken met bestaande visuele speller paradigma's. De vergelijking vindt plaats zowel op het niveau van de classificatie als de hersensignalen die daaraan ten grondslag liggen. De vingertoppen van gezonde proefpersonen werden gestimuleerd met korte mechanische tikjes terwijl het EEG gemeten werd. De letters van het alfabet waren toegekend aan verschillende vingers en proefpersonen konden een letter selecteren door in zichzelf het aantal tikjes op de betreffende vinger te tellen. De prestatie van de door ons ontwikkelde tactiele speller werd vergeleken met de drie typen visuele spellers, te weten: de overte en coverte aandachtsvarianten van de visuele matrix speller en de coverte aandacht Hex-o-Spell speller. Dit hoofdstuk laat zien dat het mogelijk is een tactiele speller te gebruiken voor communicatie. De tactiele speller vormt een bruikbaar alternatief voor de visuele speller, in het bijzonder voor mensen die hun ogen niet meer goed kunnen richten.

Hoofdstuk 4 richt zich op het detecteren van semantische priming op het single-trial niveau. Priming zou gebruikt kunnen worden om door een semantisch netwerk te bewegen en zo te achterhalen welk woord iemand wil communiceren. Door gebruik te maken van machine learning technieken is het mogelijk om korte stukjes hersenactiviteit te analyseren en classificeren als gerelateerd of ongerelateerd. Dit zou bijvoorbeeld gebruikt kunnen worden om een Brein-Computer Interface te bouwen. Het hoofdstuk beschrijft een experiment waarbij proefpersonen woordparen te zien krijgen en ze gevraagd wordt of deze woorden gerelateerd zijn of niet. Er werd een classifier getraind om te bepalen of proefpersonen woorden als gerelateerd of ongerelateerd beschouwden. Deze beslissing werd gebaseerd op één seconde aan EEG data. Het hoofdstuk toont aan dat semantische priming significant boven kansniveau gedetecteerd kan worden bij alle proefpersonen.

Hoofdstuk 5 onderzoekt een mogelijke BCI gebaseerd op semantische relaties. Zoals in de vorige paragraaf genoemd is, kunnen semantische relaties gebruikt worden om door een semantisch netwerk te bewegen. De BCI zoekt uit welk prime woord een proefpersoon in gedachten heeft door probe woorden te presenteren die geselecteerd worden door een intelligent algoritme. Proefpersonen geven aan of een gepresenteerd probe woord gerelateerd is aan hun prime woord door een enkele vingerbeweging. De detectie van het neurale signaal dat geassocieerd is met deze beweging wordt door de BCI gebruikt om het prime woord te decoderen. De bewegingsdetector combineert zowel de opgeroepen als geïnduceerde respons veroorzaakt door de beweging. Het hoofdstuk toont aan dat het intelligente algoritme gebruikt voor de presentatie van de probe woorden een significant hogere prestatie oplevert dan een willekeurige selectie van probe woorden. Simulaties demonstreren dat de BCI ook werkt met grotere woordenboeken.

Dit proefschrift heeft verscheidene mogelijkheden tot verbetering van de visuele speller onderzocht. Dit is gedaan door gebruik te maken van betere stimulus codering, geschiktere modaliteiten voor stimulatie of door het detecteren van hogere orde concepten. Al deze verbeteringen lijken veelbelovend, maar geen van deze verbetering is de magische oplossing die bruikbare BCIs tot een realiteit maakt. Hoewel het in feite duidelijk is dat BCIs voor patiënten nuttig zullen zijn, is het ook duidelijk dat er nog veel onderzoek nodig is voor ze een alternatief kunnen vormen voor bestaande communicatie modaliteiten. Het zal dus nog een tijd duren voordat de BCI thuis gebruikt kan worden door de patiënten die ze nodig hebben.

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Curriculum Vitae

Jeroen Geuze was born on the 23rd of September in Zaandam. His academic career started in 1999 when he graduated from high school (VWO) and started his Bachelor studies in Artificial Intelligence at the Vrije Universiteit Amsterdam. After obtaining his Bachelor's degree he started his Master's studies, also in Artificial Intelligence at the VU. He specialized in Knowledge Management & Knowledge Technology and Intelligent Internet Applications. During his thesis he researched the possibilities of an intelligent tutoring agent that could help children learn to negotiate. In 2005 he moved to Nijmegen to obtain his second Master's degree in Cognitive Neuroscience. In the first year of the two-year program he specialized in Psycholinguistics, but during the internship in his second year, he pursued a combination of Artificial Intelligence and Cognitive Neuroscience: Brain Computer Interfaces. After obtaining his second Master's degree he started his PhD research in the same topic.

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